Market Knows Best: The Not So Hidden Risks of Private Ratings

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Abstract

We implement a new methodology to measure credit rating inflation that separates default risk from liquidity risk, using private letter ratings (PLRs)—ratings disclosed only to the paying investor. After a proposed capital charge reform, the most affected life insurers drastically increased PLR usage, raising regulatory arbitrage concerns. We estimate that bonds with PLRs carry additional risk equivalent to three rating notches, supporting the arbitrage explanation. Our new methodology reveals a substantial part of this rating inflation is explained by decreased liquidity rather than hidden default risk.

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Keywords: Private Credit, Life Insurance, Private Placements, Annuities, Private Equity, Credit Ratings, Rating Inflation.

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1 Introduction

A public and independent credit rating reduces information asymmetries for all financial market participants, facilitating investment and trading decisions. Recently, private letter ratings (PLRs), available only to the paying party, have emerged as an alternative to public ratings. The lack of public disclosure of the assessment of financial risks in PLRs undermines the information transmission to markets. Investors using PLRs to rate their holdings claim that evaluation standards are rigorous and cite keeping sensitive information private as the only reason for their usage (Zawacki 2026). Detractors, however, describe PLRs' methodologies as lenient, pointing to ratings inflation as the main driver of their rapid proliferation (Tucker et al. 2025).

In this paper we develop a novel methodology to assess rating inflation accounting for liquidity risk, and we use it to test alternative explanations for the proliferation of PLRs usage in the insurance industry. Our methodology proposes using bonds' ex-post performance as a measure of default risk and bonds' price sensitivity to trading volume as a measure of liquidity risk. The methodology estimates differences in these two dimensions between bonds expected to experience inflation and bonds expected to have an accurate rating.[1] Differences in ex-post performance capture rating inflation, i.e. the extent to which a given rating downplays the risk of default. On the contrary, differences in the sensitivity of price to volume capture the liquidity risk effect, which does not constitute inflation as ratings are only designed to predict default.

We use our new methodology in the aftermath of the 2017 National Association of Insurance Commissioners (NAIC) proposal to change the capital charges for insurers' investments. This change resulted in losers, that suffered a larger increase in their required capital, and winners, that experienced a smaller increase in their required regulatory capital . To comply with the new regulation, losers had incentive to improve their investments' ratings, which could be achieved through buying safer bonds or through inflating risky bonds' ratings. Over this time frame, life insurers' PLR investments grew ten-fold reaching \$478 billion in 2025, equivalent to 8 percent of their general account assets (see Figure 1). If the usage of PLR was to keep information private, we would expect winners and losers to use PLRs similarly. However, if the motivation for PLR usage was

[1] We also control for a broad set of observables characteristics that could affect liquidity and default.

rating inflation, we would expect that losers would use PLRs more intensively. We find strong evidence that losers, insurers facing higher capital charges, increased their PLR usage more than winners after the announcement of the regulatory change. This finding moves us towards the rating inflation hypothesis over the private information protection hypothesis. However, in order to confirm the inflation hypothesis we need to disentangle default (inflation) from liquidity, which we do by implementing our new approach.

As a first step, we evaluate how much riskier the market perceived PLR bonds to be relative to public rating bonds, where risk perception is measured as the spread over the risk free rate after controlling for bond characteristics. We estimate a 126 basis point spread difference between insurers' new bond purchases with a PLR and their purchases with a public rating.

Subsequently we evaluate the contributions of default and liquidity to this risk perception difference. We find that, controlling for rating classification, during our 2020 to 2025 sample period PLR bonds are 0.5% more likely to default than comparable public rating bonds, which is equivalent to a 1 rating notch of inflation. This difference increases to 1.3% when considering only investment grade bonds equivalent to 3 notches of inflation. In the liquidity risk dimension, we find that the observed price sensitivity to trading volume is an order of magnitude larger for PLR bonds relative to bonds with a public rating. This difference is statistically and economically significant. For example, selling the totality of a bond issue requires an additional 50 basis point spread discount for PLR bonds. Together, these results suggest that differences in liquidity risk and differences in default risk between bonds expected to have rating inflation and bonds expected to have an accurate rating, in our setup, are of the same order of magnitude.[2] Hence, omitting liquidity risk differences would results in a substantial overestimation of rating inflation by attributing higher spreads due to higher liquidity premium to higher default premium.

Our setup is particularly appealing for testing our new approach. Life insurers are large investors in public and private corporate bonds that are exposed to substantial default and liquidity risk. Furthermore, insurers have to disclose detailed issuer level holdings data to the regulator providing us with a comprehensive set of information for

[2] We note that some of the liquidity premium in PLR securities may be due to the PLR itself. The lack of public disclosure might make it harder to price and trade assets with this type of rating and thereby reduce the liquidity in PLR securities.

an accurate statistical analysis. In addition, the proposal of a new capital rule in 2017 (that went into effect in 2021) created strong and heterogeneous incentives for insurers to pursue higher ratings in their investments. And the surge of private letter ratings, with fewer disclosure requirements, reduced the cost for insurers to obtain inflated ratings relative to pursuing a true reduction of credit risk in their bond portfolios. Nonetheless, concerns might still exist that PLR usage and/or rating inflation during this period was caused by broad changes in financial markets and not by the regulatory reform.

We use an instrumental approach to confirm the causality link between the regulatory change and the proliferation of PLRs and corresponding rating inflation. We chose the exposure to the regulatory reform as the instrument for incentives to regulatory arbitrage (rating inflation), measured as the capital charges with the new methodology less the capital charges with the pre-reform methodology. This measure is larger for insurers with riskier investments within the less granular pre-reform capital charges' categories, and hence resembles the reach for yield measure of arbitrage described in Becker and Ivashina (2015). Following Irani et al. (2021) we calculate our instrument using holdings data *at the time* of the capital reform announcement to reduce downward bias from anticipation effects. We find that the instrument is significantly correlated with a greater investment in PLR bonds for large insurers as early as 2018, consistent with regulatory arbitrage driving PLR usage and also with a strong anticipation effect of the 2021 regulatory change.

We contribute to several strands of the ratings literature. First, we complement the literature describing changes in rating incentives associated with the party paying for the evaluation. While in the past ratings paid by investors have been reported as more conservative than those paid by the issuer (Jiang et al. (2012) and Liu et al. (2023)), in our setup the changing regulatory environment puts pressure on investors to pursue inflated ratings. Consistent with this pressure, bonds with a PLR, that are vulnerable to inflation, have substantially higher default risk compared with bonds less subject to inflation, even though investors were paying for the rating. We also show that bonds with inflated ratings have a much higher liquidity premium that needs to be accounted for in order to measure inflation accurately. As such, our paper is closer in spirit to Bongaerts et al. (2012) who establish a link between better information and bond turnover. We complement the turnover analysis by adding a measure of price sensitivity to trading volume which captures liquidity risk more directly.

We also contribute to extant work on rating inflation associated with agencies' market competition (Griffin and Tang (2012), Griffin et al. (2013) and Becker and Milbourn (2011)) and rating inflation due to ties between the issuer and the rating agency (Efing and Hau 2015). Our contribution to this literature is disentangling different mechanisms through which rating inflation can affect financial regulation and financial markets.

Contemporaneous research has argued that private letter ratings have proliferated among insurers and are associated with strong rating inflation (see for example Li et al. (2026) and Gschossmann et al. (2026)). In a similar vein, the proliferation of PLRs might be the consequence of entrant PL specialized rating agencies providing advantageous ratings to gain market share combined with insurance firms seeking to offset regulatory changes that increased capital charges Harris et al. (2025). These concerns have captured wide attention among practitioners (see for example Tucker et al. (2025)). Our novel methodology helps measuring this inflation more accurately by decomposing the bias into a default and a liquidity component. We show that this distinction is crucial avoid overestimating rating inflation.

Our findings also complement a large body of work on the strategic use of regulatory rules. Specifically, we find that insurers use PLRs to reduce capital charges without reducing their risk exposure. A similar conclusion is reached in Drexler and Granato (2026). However, in their setup insurers use accounting exceptions to increase their accounting capital, while in our setup the regulatory arbitrage is achieved through reducing the regulatory requirements. Our results also complement studies on regulatory arbitrage in other contexts of insurance regulation (see for example Becker and Ivashina (2015), Kirti and Sarin (2024), Koijen and Yogo (2016a) and Carlino et al. (2025)). Finally, our results are consistent with a broad literature showing how banks have used regulatory loopholes to navigate more stringent capital regulations (see for example Jones (2000), Acharya et al. (2013), Plosser and Santos (2018) and Behn et al. (2022)).

The remaining of the paper is structured as follows: section 2 describes the data and defines the variables used in the study. Section 3 explains our empirical approach and presents our results. We conclude in section 4.

2 Data

2.1 Institutional Background

In the United States, insurance companies are regulated at the state level, however the National Association of Insurance Supervisors (NAIC) coordinates regulation across states and hence most regulation is common across states. The goal of this regulatory system is to protect consumers and promote insurer financial solvency, so insurers are able to cover their policyholder obligations. Generally speaking insolvency risk is a combination of liability risk, which is the risk that insurers' obligations with policyholders and creditors increase in value, and asset risk, which is the risk that their assets decrease in value.

To protect life insurers' solvency and the funds available to pay claims on long-duration life and annuity contracts, state regulators impose capital requirement on the assets held by insurers. The asset side risk is proportional to the probability of default of each asset, hence the the required capital increases when insurers invest in riskier assets. The specific amount of capital insurers are required to hold for each particular asset is called a capital charge. For regulatory purposes, the probability of default is estimated based on the credit risk rating of the assets. Therefore, the extent to which capital charges reflect risk correctly, depends on the accuracy of their holdings' credit ratings.

Besides these asset specific capital charges, required capital also depends on the underwriting risk of the written policies, which is called insurance risk, on interest rate risk, and on business risk. Insurance risk is a function of the variability of the payments that policyholders would receive in each state of the world. Interest rate risk is a function of the mismatch between the cash flows of the assets and the cash flows of the liabilities. If these cash flows were identical, any fluctuations in the interest rate would be innocuous for insurers. However, if the cash flows are not identical, fluctuations in interest rates, a crucial component of the discount rate, could affect assets and liabilities' value differently. Potentially, these interest rate driven changes could result in liabilities' value being higher that assets' value, compromising the ability of the insurer to honor its obligations. Business risk reflects insurers' operations unrelated to the other three risks. In this paper we focus only on the asset side risk.

The exact capital requirement for each insurer is determined by a risk-based capital (RBC) formula, which estimate a minimum level of capital based the risk factors, where capital is estimated using insurers' statutory accounting rules.[3] Consistent with the associated risks, RBC charges are split into four major categories: C-1 Asset Risk, C-2 Insurance Risk, C-3 Interest Rate Risk, and C-4 Business Risk. One of the most important determinants of a life insurer's required capital is the C-1 charge on long-term bonds, as they comprise over 60 percent of the industry's assets.

The C-1 charge for a given bond is a function of its credit rating, which determines the percent of the bond's carrying value that the insurer must hold as capital to support potential losses.[4] As shown in Table 1, prior to 2021, credit ratings and their associated capital charges were split into 6 NAIC designation categories. This coarse rating split, which, for example, applies the same capital charge to AAA and A- rated bonds, created an incentive for insurers to invest in the lower tranches of a given NAIC designation to achieve a higher capital-adjusted yield, as documented in Becker and Ivashina (2015). Beginning in 2020, after nearly a decade of work the NAIC expanded this 6 category designation to a granular 20 notch system. The new capital charges went into effect as of year-end 2021.[5] In the new system, each NAIC designation corresponds to a notch rating used by a Nationally Recognized Statistical Rating Organizations (NRSROs), such as Moody's, A.M. Best, and Demotech.[6] This increased granularity created better alignment between capital charges and the credit risk of insurers' bond portfolios. However, since the NAIC's Security Valuation Office (SVO) must accept the rating given by an NRSRO, the success of the increased granularity in improving capital charges' estimation, strongly depends on the accuracy of individual credit rating providers.

2.1.1 Private Letter Ratings

Historically, ratings issued by traditional credit agencies made the rating available to all the participants in the financial markets after issuance. However, in recent years a new type of rating, provided only to the paying party, has become an alternative to

[3] NAIC Risk-Based Capital.

[4] The C-1 charge also includes a covariance adjustment that increases capital charges for undiversified portfolios and reduces it for diversified portfolios.

[5] Risk-Based Capital Charge Requirements on Fixed Income Assets to Change

[6] List of Nationally Recognized Statistical Rating Organizations.

traditional public ratings. These ratings called private letter ratings (PLR), receive the same treatment and capital charges as public ratings under the implicit assumption that they reflect the same information. Nonetheless contemporaneous academic research as well as practitioners reports have questioned this implicit assumption (see for example Aquilina et al. (2025), Tucker et al. (2025), Li et al. (2026) and Gschossmann et al. (2026)).

Given the importance of credit ratings in the more granular NAIC designation framework, the NAIC also sought increased oversight into this recent private credit rating. An NAIC designation is obtained by an insurer filing a security with the SVO in accordance with the Purposes and Procedures Manual of the NAIC Investment Analyses Office (P&P Manual).[7] Since 2018, a number of amendments to the P&P Manual have increased the oversight of the SVO into PLR securities.

1. Effective for the 2019 year-end filings, insurers were required to provide proof of a rating for any PLR security issued after January 1st, 2018. The rating must be shared with SVO by either the insurer or the credit rating provider, it must be security specific, and updated on at least an annual basis.[8]

2. Effective January 1, 2022 insurers must provide the SVO with the private letter rationale reports for each PLR security. The rationale reports must be provided both at the time of investment and annually thereafter, but there are no penalties for non-compliance until January 1, 2024. After that date insurer will have to rate the security as 5GI if they cannot provide the rationale report.[9][10]

3. Effective January 1st 2026, state regulators & NAIC staff will have the ability to contest credit ratings if the believe the credit rating is not a reasonable assessment of investment risk.[11] In doing so the NAIC and SVO may consider the following observable factors:

    (a) a comparison to peers rated by different CRPs,

[7] Purposes and Procedures Manual of the NAIC Investment Analyses Office as of December 2025

[8] New NAIC Rules on Private Letter Ratings - ACIC

[9] A designation of 5GI is equivalent to a CCC rating and carries a 23.8% capital charge.

[10] Make (Whole) A Minute: The New Burden of Proof for Private Ratings — Akin Gump Strauss Hauer & Feld LLP

[11] Credit Rating Challenge Proposal

(b) consistency of the security's yield at issuance or current market yield to securities with equivalently calculated NAIC designations rated by different CRPs

(c) the SVO's assessment of the security applying based on relevant methodologies

(d) any other factors deemed relevant.

2.2 Data Sources

Our analysis draws on detailed regulatory data of U.S. life insurers' asset holdings and balance sheets from 2017 to 2025 accessed from S&P Capital IQ Pro. Our core analysis uses Schedule D Part 1 of the National Association of Insurance Commissioners (NAIC) statutory filings, which provides asset-level information on all long-term debt securities held by U.S. life insurers on an annual basis. We gather additional insurer level balance sheet and regulatory information from the *Balance Sheet* and *Capital Adequacy* summary highlights of the filings. We gather information on life insurer reinsurance transactions from Schedule S and quarterly securities sales and disposals from Schedule D part 4 of the regulatory filings. In the following sections we detail how we utilize the regulatory data to construct the datasets used for our analyses.

2.2.1 PLR Spreads and Defaults

Our primary analysis employs a security-level cross-section of year-end bond holdings from 2020 to 2025 constructed using Schedule D Part 1 of the annual filings. . Importantly we identify publicly rated and privately rated securities using the SVO adminstration symbol. PLRs are identified with a "PL", while securities with publicly available ratings are reported with an "FE" under the SVO guidelines. Then to create our cross-section we restrict the sample to insurer-bond observations in the earliest quarter the bond is purchased in the data. We observe 535,090 insurer bond purchases with a PL or FE designation, between 2020Q1 and 2025Q4 of which 341,287 occur in the earliest quarter of purchase and 111,593 are unique securities. We use only a single observation per security, so as to not overweight more widely held securities in our analysis We only keep observations where insurers report either of these symbols. This further reduces our sample to 86,017 observations of which 10,190 are PLRs and 76,260 have an FE designation.

Our analysis uses the rating and yield in their earliest quarter of purchase as a proxy for yield and rating at the time of issuance. We observe ratings on an annual frequency and notch ratings are first reported in the year-end 2020 data. We calculate the purchase price, as the actual cost divided by the par value. Where the actual cost is defined as the cost of acquiring the security including broker commission and other related fees, excluding accrued interest and dividends. We calculate the yield as the price times interest rate at issue and create a spread using a maturity matched treasury rate in the quarter of purchase.

We classify securities into bonds and asset-backed securities (ABS) using issuer and issue-level details reported in NAIC Schedule D filings. Corporate securities are identified using the issuer type variable, which indicates whether the issuer is a corporate, municipal, or U.S. government issuer. Because insurer-reported issuer types are occasionally inconsistent, we assign the most frequently reported type for each nine-digit CUSIP across all filings.

To distinguish between bonds and ABS, we rely on the annually reported asset type field. Securities are classified as corporate bonds if the asset type is listed as "long-term bond", "issuer credit obligation (ICO)" or a closely related category; asset-backed securities are identified where the asset type is listed as "asset-backed security" or similar. As with issuer type, we assign each security the most commonly reported asset type across insurers to ensure consistency.

Following Meisenzahl et al. (2026), we identify privately placed securities using the special character in the 6th-8th place of the CUSIP and use the same matching algorithm to identify issuer industries. We also follow Meisenzahl et al. (2026) to identify issuer industry using information from S&P Capital IQ's company database and Dun & Bradstreet National Establishment Time Series (NETS) database for information on private firms (e.g., firm name, industry, and corporate parent details), and Mergent's Fixed Income Securities Database (FISD) accessed via Wharton Research Data Services (WRDS) for information on public issuers. We separate bond issuers into the following broad industry categories: non-financial, financial, real-estate, utility & infrastructure, and unmatched.

We also identify additional characteristics expected to affect bonds spreads and default rates using the Schedule D holdings. We identify the capital structure: senior secured, senior, subordinated, or no-info; whether a security is callable, whether the security is variable rate; issue size as measured by par value of industry holdings, and original maturity at purchase in years. Our measure of default treats any bond that is reported with an NAIC designation of 6 as defaulted. The NAIC 6 designation category includes securities with CC to D equivalent ratings. [12]

When we collapse from the insurer-CUSIP to CUSIP level data we make the following decisions: we use the mean spread and yield at purchase, use the worst/lowest rating at earliest purchase, and consider a bond PLR if any insurer records a "PL" in the SVO designation symbol at earliest purchase.

2.2.2 Insurer Characteristics

To understand the characteristics of insurers who invest in PLR rated securities we gather balance sheet and regulatory information from the life insurance statutory filings obtained from S&P Capital IQ Pro. We compile a dataset of 683 life insurance companies between 2017 and 2025. From the annual reports we get general account assets as a measure of size, the authorized control level risk based capital (RBC) ratio, return on assets, total reserves, annuity reserves, indexed annuity reserves, and a dummy for if the insurer is a stock company. We also gather characteristics that are associated with regulatory arbitrage: alternative investments from Schedule BA and affiliated investments from the balance sheet. From the Schedule D data we create aggregate measures of risky securities holdings: PLR, high-yield, collateralized loan obligations (CLO), and private placements. Using Schedule S we also track life insurers reinsurance relationships and identify reserves ceded to foreign affiliates and captives following Koijen and Yogo (2016a)). To calculate the credit rating composition of insurers' public corporate bond portfolios prior to 2020 we rely on S%P and Moody's credit ratings provided from Mergent FISD provided by WRDs. We once again, follow Meisenzahl et al. (2026) to identify insurers owned by private equity.

[12] According to S%P a CC rating indicates that the entity is in distress and may not be able to meet its obligations; a C rating indicates the issuer is struggling to meet its obligations; and a D rating indicates entity is unable to meet its financial obligations.

2.2.3 Sales and Transactions

For the analysis of liquidity risk we utilize information from Schedule D Part - 3 which is a quarterly report of long-term securities disposed. The sales we observe are secondary market transactions between the insurer and another buyer. This schedule includes information on the date of disposal, amount disposed, and a vendor name describing who the transaction was with. To determine the sale price we use the actual cost disposed divided by par value disposed. We use the vendor variable to separate sales and non-sales, such as calls, redemptions, and pay downs, and buyer types We split the transactions by buyer types into direct transactions, broker transactions, and various transactions. Broker dealers include large banks such as Citi or JP Morgan, and as shown in Fournier et al. (2024), for private placements smaller specialty brokers like the StoneCastle Securities or the Seaport Group. Brokers provide liquidity, as their balance sheets can absorb large sales and can arrange trades more easily. Direct transactions are arranged by the insurer with another party such as a pension fund. "Various" transactions are typically multiple trades combined into one reported disposal.[13] We control for any changes in the quality of the bond using two measures of market risk. First, we use the notch credit rating in the period prior to the sale to control for credit quality. Second, we use the maximum percent of the bond value reported as impaired in the prior period or period of sale to control for price changes due to changes in bond default risk.

3 Methodology and Results

In this section, we demonstrate that private letter ratings do not convey the same risk information as public ratings and detail the implications of this finding for market efficiency and life insurer capital regulations. To show the possible existence of rating inflation, we first estimate if otherwise equivalent PL and public rated bonds earn the same spread over the risk-free rate and find that PL rated bonds earn a higher spread providing suggestive evidence supporting rating inflation. Next, we show that PLRs, on average, do not convey the same default-risk information as a public rating and are therefore inflated. However, markets look-through this rating inflation and price the

[13] Disposals listed as "Various" are typically multiple trades that are aggregated

excess default risk correctly. We then show that higher expected defaults only explain a portion of the PLR spread premium and test whether PLRs affect asset prices through dimensions besides default risk, in particular through liquidity risk. We show that PL rated bonds have higher liquidity premium than equivalent public rated bonds and argue this liquidity premium is driven by opacity and lack of credibility of PLRs. We believe the bias itself is, at least in part, the reason why markets distrust PL ratings. Finally, we show that insurers took advantage of this rating inflation and strategically used PLRs to reduce their capital charges and increase their capital-adjusted returns.

3.1 Price Effect

Credit ratings are designed to inform market participants about the likelihood of future default. While bond prices reflect information about both credit risk and liquidity risk. If private letter and public ratings convey the same information about these risks, then other things being equal, two bonds in the same risk rating category would have the same price. However, if the market believes private letter and public ratings convey different default or liquidity risk information then bond prices, for the same rating notch, might depend on whether the rating is private or public. We test whether the price of PL rated bonds and the price of public rating bonds in the same rating notch are equal, where price is expressed as a spread over the risk free interest rate.[14] Using this method we find that PL bonds earn 126 higher spreads than comparable public rating bonds suggesting potential rating inflation.

First, in Figure 2 we present our main result using a histogram that overlaps the spread distribution of PL rated bonds with the spread distribution of public rating bonds. This visual representation provides an intuitive way to assess potential distortions. These histograms are presented independently for bonds with a rating of A and for bonds with a rating of BB. This allows us to determine whether potential bias varies across rating notches.[15] In Panel A of Figure 2 we present these distributions using spread decile buckets estimated within the same credit rating category. The distribution for PL rated bonds is in maroon and the distribution of public rating bonds is in navy

[14]We transform the price of bonds with different maturities into a comparable spread over the risk free rate using the treasury bond of similar maturity as the risk free instrument.

[15]The histograms for the remaining rating notches are presented in figures 7 and 9 in the appendix.

blue. Because the deciles are estimated within the same rating, if the spread distribution of PL rated bonds and the spread distributions of public rating bonds were the same, then both histograms should look identical. Furthermore, since rating notches should reflect a similar level of risk these "within rating" histograms should resemble a uniform distribution. In the plots, the spread distribution for public rating bonds is close to uniform. However, the distribution of spreads for PL rated bonds is strongly shifted to the right. This shift indicates that within the same credit rating, the risk perceived by the market for PL rated bonds is, on average, much larger than the risk perceived for publicly rated bonds.

In Panel B of Figure 2 we again compare the distributions but use deciles constructed at the full sample (AAA to B- rated) level. Assuming that markets price default risk correctly, and that ratings are an informative signal of default risk, we should observe that A rating notch bonds, that are safer compared to the average, have spreads concentrated in the lower end of the spread distribution (left-side). We should also observe that BB notch credit rating bonds have spreads concentrated in the higher end of the distribution, and intermediate rating notches, displayed in the appendix, should be denser in the middle of the distribution. The distribution of spreads for public rating bonds is as expected; A-rated bonds have a spread distribution shifted to the left, while BB rating notch bonds have a spread distribution shifted to the right.[16] However, the spreads' distribution of PL rated bonds (maroon bars) is consistently shifted to the riskier portion of the distribution on the right compared to publicly rated bonds (navy bars). PL A-rated bonds have spreads concentrated in the center of the distribution, and the weights in the left and right tail of the distribution are similar. This distribution not only confirms the observation from the first half of the figure, that PL rated bonds are riskier, but also indicates that PLRs are much less informative about market perceived risk than public ratings. Intuitively, the concentration of weights in the middle of the distribution and the similarity between left and right tail means that knowing that a PL bond is A-rated tells you very little about the market perceived risk. The PL BB-rated bond spread distribution is also shifted to the right relative to the spread distribution of publicly rated bonds, confirming that PL rated bonds are perceived as riskier. However, the

[16] Also as expected, riskier investment grade (BBB-rated) displayed in figure 7 in the appendix, have a distribution with weight concentrated in the center.

distribution is concentrated to the right as expected, which suggests high-yield PLRs , while also biased, are more informative about risk exposure than investment grade PLRs.

The histograms are complemented with an OLS fixed effect regression that estimates the average magnitude and statistical significance of the spread difference. We estimate the following cross-sectional regression on the CUSIP level using bonds purchased by life insurers between 2020Q1 and 2025Q4 based on observations in their earliest quarter of purchase, as a proxy for primary market purchases. We estimate this using equation 1:

$$Spread_c = \alpha + \beta_1 \mathbb{1}_{\text{PLR}_c} + \beta_2 \mathbb{1}_{\text{PP}_c} + \beta_3 \mathbb{1}_{\text{Public ABS}_c} + \beta_4 \mathbb{1}_{\text{PP ABS}_c} + \gamma X_c + \epsilon_c \quad (1)$$

where $X_{c,t}$ is a vector of bond controls that include dummies for rating notch, origination quarter, maturity at purchase in years, callable, floating rate, and credit seniority, as well as log par value held by insurers as a measure of issue size. The coefficients on the indicator function capture the additional spread over publicly traded bonds for PLR (β_1) and standard errors are clustered at the origination quarter level.

Table 2 presents the results of this OLS model. In the first column of Table 2 we observe that on average across the whole sample bonds with a PL rating have 126 basis point higher spread over the risk free rate relative to the spread of bonds with a public rating. To put this number in context, insurers A- and BBB- public rated bond holdings had 167 and 287 basis point spread at purchase respectively, a gap of 120 basis points (see Table 7). So the spread gap between PL rated bonds and public rated bonds is roughly equivalent to three full rating notches. In the second and third columns of Table 2 we observe that the spread difference between PL rated bonds and public rated bonds is 120 and 145 basis points respectively for the investment and non-investment grade samples. Given that the average spread of publicly rated bonds in the sample is 196 for IG and 483 for Non-IG our findings indicates that potential for rating inflation, as a proportion of the unbiased spread, is stronger in investment grade PLRs.

In Table 3 we add interactions between bond characteristics and the PLR dummy variable. This interactions tests whether the PLR spread premium is larger among certain types of bond issues. The regression is shown in equation 2

$$Spread_c = \alpha + \sum_{j=1}^{4} \beta_j D_{jc} + \sum_{k=2}^{4} \delta_k (\mathbb{1}_{\text{PLR}c} \times Dkc) + \gamma X_c + \epsilon_c \tag{2}$$

where $D_{1c} = \mathbb{1}\text{PLR}c$, $D2c = \mathbb{1}\text{PP}c$, $D3c = \mathbb{1}\text{Public ABS}c$, $D4c = \mathbb{1}\text{PP ABS}_c$. In this regression, the only interactions between bond characteristics and the PLR dummy variable that have relevant explanatory power on bond spreads are the bond's issuance type (publicly issued or private placement) and whether the bond is a structured instrument or a corporate bond (ABS or bond). For brevity, we only report the betas on the interactions with predictive power, however all observable variables are still included as controls.[17] In the first column of Table 3, we observe that when running the regression for the whole sample, publicly issued bonds with a PL rating, which we use as the benchmark group, exhibit the largest PLR spread premium of 222 basis points. For public ABS bonds with a PL rating, this premium falls to 58 basis points (the sum of the benchmark 222 basis points and the interaction effect of -164 basis points). Private bonds with a PL rating show a similar premium of 59 basis points, while private ABS with a PL rating display only a 16 basis point premium that is not statistically significant.[18] In the second column of table 3 we observe that for the subsample of investment grade public bonds with a PL rating the PLR spread premium is 223 basis points, and the interaction effects are similar to those found for the whole sample. In the third column of Table 3 we observe that for the subsample of non-investment grade bonds the spread difference for public bonds with a PL rating is 229 basis points.

In this section we do not make any causal claim. We simply compare bonds with public ratings and bonds with private letter ratings that have the same credit rating and therefore the same regulatory capital charges, and then we evaluate if their market prices or spreads are statistically different. We find that bonds with PL ratings earn a higher spread and this PLR spread premium is strongest in publicly traded bonds and larger relative to average spreads in investment grade issues. In the following sections, we show

[17] The findings in (Cornaggia et al. 2017), (Griffin and Tang 2012) and (Cai and Haque 2024) are consistent with our analysis and support the use of asset class as a relevant co-variate in the analysis.

[18] While the benchmark effect of 222 basis points is significant and the interaction effect of -206 basis points is significant, the addition of the two that equals 16 basis points is not statistically different from 0 basis points.

that this private letter premium can be explained by both higher levels of default and liquidity risk.

3.2 Performance Differences

One explanation to the findings in section 3.1 is that the market perceives the credit risk of a bond with a PL rating to be higher than that of an equivalently publicly rated bond. There are two relevant questions in regards to this possible explanation and the previous analysis. First, do we observe higher levels of default in bonds with PLRs? Second, is the market risk assessment (bond spread) a better predictor of credit risk than the assessment implied by the PL rating? Third, what share of the PLR spread premium corresponds to higher levels of expected default risk and can differences in liquidity risk explain the rest?

In Table 6, we show the amount of defaults of bonds purchased by insurers between 2020 and 2024.[19] In total, 64 PLR and 172 public rating issues defaulted between 2021 and 2025. The unconditional default rate of investment grade bonds with a PL rating was 0.43% per year compared to 0.09% for publicly rated bonds. In other words, PL rated IG bonds defaulted more than four times as often. While, default rates for non-investment grade issues was slightly higher for publicly rated bonds (0.87%) than PL rated bonds (0.80%).

We test the predictive power of PLRs on ex-post observed outcome as well as the predictive power of market price (measured as spread over the risk-free rate) on ex-post observed outcomes using the specification shown in equation 3. This estimation helps us answer the first two questions raised in the beginning of this section:

$$\text{Default}_{i,t} = \beta_0 + \beta_1 \text{PLR}_i + \boldsymbol{\beta_2} \mathbf{X}_i + \beta_3 \log(\text{Par})_i + \gamma_t + \{\delta_r, \theta_s\} + \epsilon_{i,t} \tag{3}$$

Where γ_t represents origination year fixed effects, r indexes rating notches, s indexes spread ventile buckets, and $\mathbf{X}_i$ is a vector of bond characteristics including private placement status, maturity, seniority, ABS classification, floating rate indicator, plus all their interactions.

[19] A default is defined as any bond that receives an NAIC 6 category designation by an insurer, equivalent to CCC- or worse

In Column 1 of Table 5 we confirm the results from Table 6 and show that on average PL rated bonds have 0.50% higher default rate relative to publicly rated bonds after controlling for all observable variables except from the bond's rating and spread.[20] This difference is only significant at the 10% level, but it is economically large considering that the average default rate for bonds with a public rating in our sample is 0.46% (see table 6). In Column 2 we add a control for the bond's notch rating. Adding this control has no impact on our estimate, which remains at 0.5% and is statistically significant. This result suggests that PLRs do not provide relevant information about a bond's expected default beyond what we can infer by controlling for relevant observables. In Column 3 we add a control for spread over the risk free rate in place of the rating control. Surprisingly, after controlling for the bond's spread, the predictive power of being rated with a PLR on realized defaults disappears almost completely. This suggests that markets can "see-through" the biased PLRs and that the market price of PL rated bonds reflects the real risk of default and not the risk implied by the PL rating notch. The last finding is of paramount relevance as it indicates that the rating inflation from PLRs is primarily a regulatory concern and not a market efficiency concern.

In Columns 4 to 6 we repeat the analysis for the subsample of bonds with lower risk and in columns 7 to 9 for the subsample with higher risk. We define lower and higher risk bonds, as those below or above the median notch rating of BBB+ (Columns 4 to 5 & 7 to 8) or median spread of 225 basis points (columns 6 and 9).[21] We observe that for the subsample of lower risk bonds, the difference in default rate is 1.3 percentage points, which is more than double the difference using the whole sample. Again, the difference persists when adding a control for rating and disappears when controlling for spread, consistent with markets pricing default risk correctly and hence rating inflation being primarily a regulatory concern but not a source of market inefficiencies. For the higher risk bonds, being rated with a PLR provides no predictive power for realized defaults, consistent with rating inflation being more prevalent for higher rated bonds.

[20]We construct spread fixed effects by splitting the sample into ventiles. Using this approach instead of a continuous spread variable allows us to capture nonlinearities and avoid results being driven by outliers.

[21]We choose BBB+ as the subsample threshold of the heterogeneous treatment analysis in order to work with equally sized groups. This approach maximizes predictive power, which is particularly relevant for the analysis of an unbalanced binary variable. Results are similar in magnitude if using the threshold from the spread section.

In Figure 3 we provide a graphical and more intuitive representation of the results described above. Panel A displays default rates by spread decile while Panel B displays default rates by rating notch. In both panels, public ratings are plotted in navy blue while PL ratings are plotted in maroon. In Panel A we observe that for bonds with a public rating, default rates increase almost monotonically with spread decile. The association between default rate and spread decile for PL rated bonds, while less monotonic, still shows that default rates tend to be higher for bonds in higher spread deciles. In contrast, in Panel B we observe that the association between lower ratings and higher default rate only holds for public ratings, while PL rating notches are largely uninformative about default rates. Together this shows that, while PL rates default more often than bonds with comparable public ratings, market participants look through PLRs and price bonds according to their real default risk.

3.3 Liquidity Differences

Section 3.2 shows that after controlling for rating, the difference in default rates between bonds with a PL rating and bonds with a public rating is 0.5%. This suggests that default risk likely accounts for a substantial fraction, but not all of the spread gap found in section 3.1. A back-of-the-envelope estimation of the default component of the PLR spread premium can be done by using historic default rates from (S&P Global Ratings 2025) and average spreads at purchase by rating. The average bond in our sample is held for approximately 3-years so this is the time horizon we use to measure observed default rates. As seen in column 1 of Table 7 the difference in average cumulative default rates over 3-year period between a BBB and BBB- bond is 0.66 % (1.17% - 0.51%) this is roughly equivalent to our beta estimate of 0.5%. While observed difference in spreads for public rated BBB and BBB- bonds is 57 basis points. Thus, while higher expected default rates of PLR bonds likely explains a substantial portion of the estimated 126 basis PLR spread premium found in section 3.1, there may be other sources of the spread gap.

In this section we evaluate the extent to which liquidity risk can explain the remainder of the PLR spread premium. Since we aim at capturing the risk involved in selling an existing holding, we restrict observations to secondary market sales. Focusing on secondary market transactions raises concerns of self selection as the choice to sell a bond is endogenous. However, companies that sell bonds to meet cash needs usually chose the most liquid bonds first. Hence, self selection in our estimation will bias our results towards zero, making any liquidity effect we find a lower bound.

We first check whether PL rated bonds trade less often than their publicly rated counterparts. To do this we plot yearly sales as a fraction of the total holdings for PL rated bonds and public rating bonds using observed sales from the Schedule D transaction data. We separately display the sales for the main four asset classes: public ABS, private ABS, public corporate bonds and private placement corporate bonds, and split each class between private letter rated bonds and publicly rated bonds. Given that bonds with higher liquidity costs will typically be more costly to sell, investors in general have less incentive to trade illiquid bonds. So our expectation would be that if liquidity risks explains the difference in spreads then PLR bonds would trade less than their publicly rated counterparts. In the left half of Figure 4 we observe that public structured bonds with a public rating sell slightly more than public structured bonds with a PL rating, consistent with PLR bonds being less liquid. However, among private structured bonds, the ones rated with a PLR have on average higher trading volume relative to the ones with a public rating. In the left side of Figure 4, we present the sale volume for corporate bonds. We observe that public corporate bonds with a public rating trade more than public corporate bonds with a PL rating, but again, among private corporate bonds those with a public rating have lower trading volume relative to those with a PL rating.

In Table 12 we show the secondary market sales channels separately for each asset class and how those channels differ between bonds with PL and public ratings. The three channels we identify that have relevant implications for liquidity are broker dealers, direct transactions, and ”various” transactions. We believe asset classes without strong presence of broker-dealers will be the most illiquid, as broker dealer balance sheets can absorb large sales and can arrange trades more easily. Panel A show that for public bonds with a public rating 76% of sales are performed with a broker dealer, such as Citi or JP Morgan, while just 8% are done in a direction transaction. By contrast just 21% of public bonds with a PLR were sold through a broker, 43% were in a direct transaction and the remaining 43% were done through a ”various” transaction. The transaction channel mix for public bonds with PLRs looks more similar to that of private placements bonds where just 12% of PLR and 21% of Non-PLR sales are done through a broker. This findings help understand the results in Figure 4, and provides us with an additional set of relevant controls to be included in the remaining of our liquidity premium analysis.

Lower trading volume frequently has a positive correlation with liquidity risk. However, liquidity risk is a measure of the the price discount incurred when selling a substantial amount of a given asset. In some contexts, the price difference between primary and secondary markets is also considered a component of the liquidity premium. Some bonds might have low trading volume while still being liquid in the sense that their price is not strongly affected by large sales and/or that secondary market and primary market prices do not differ significantly.

A measure that captures liquidity risk more directly than trading volume is the degree to which sales volume affects sale price, and the degree to which primary market and secondary market prices are different. We use an OLS approach to estimate how these measures of liquidity risk depend on whether the rating is public or private. In addition to the control variables used throughout the paper, in the remaining of this section we add controls to capture differences in sales' channels as per our findings on Table 12. We also control for primary market prices. Hence, any price differences found in the analysis below can be attributed to either price sensitivity to trading volume or a primary-secondary market spread. Additionally, we control for potential changes in the credit quality of the asset in two ways. We use the rating in the period prior to sale and the maximum percent of bond value reported as impaired in the prior period or period of sale.

We formally define liquidity risk as the sensitivity of asset price, measured as the spread over the risk free rate, to sales' volume, measured as sales as a fraction of maximum par value held by life insurers plus the price difference between primary and secondary markets. In our regressions the beta on the PLR dummy variable captures any difference in the primary-secondary market spread between bonds with a public rating and bonds with a PLR. The beta on sales volume captures the sensitivity of spread to volume for bonds with a public rating, and finally the beta on the interaction between sales volume and the PLR dummy captures the difference in the sensitivity of price to volume between bonds with a public rating and bonds with a PL rating. Formally, these betas are estimated using Equation 4:

$$
\begin{aligned}
\text{Spread}_{i,t} = & \beta_0 + \beta_1 \text{PLR}_i + \beta_2 \text{PV Pct}_{i,t} + \beta_3 (\text{PLR}_i \times \text{PV Pct}_{i,t}) \\
& + \beta_4 \text{Price}_{i,t-k} + \beta_5 \text{Spread}_{i,t-k} + \beta_6 \text{Treasury Rate}_t \\
& + \mathbf{X}'_{i,t} \boldsymbol{\gamma} + \mathbf{Z}'_i \boldsymbol{\delta} + \alpha_\tau + \epsilon_{i,t}
\end{aligned} \tag{4}
$$

where PV Pcti,t is the percentage sold of the total par value held by life insurers , $\mathbf{X}i,t$ is a vector of transaction controls, $\mathbf{Z}i$ is a vector of bond controls, $\alpha\tau$ represents quarter-of-sale fixed effects, and standard errors are two-way clustered by quarter of sale and bond (CUSIP). We estimate equation 4 on a sample of bonds sold by life insurers with a rating of BB- or better.

In Table 8 we present the results of our empirical approach to capture the difference in liquidity premium between bonds with a public rating and bonds with a PL rating. In rows 1 (mean) and 2 (sd) we present the difference in the primary-secondary market spread gap between bonds with a public rating and bonds with a PL rating. In rows 3 and 4 we present the sensitivity of spread to volume for sales of bonds with a public rating and in rows 5 and 6 we present the difference in the sensitivity of price to volume between bonds with a public rating and bonds with a PL rating.

In the first row of column 1 of Table 8 we observe that having a PL rating is associated with a 11 basis points higher primary-secondary market spread, although the result is not statistically significant. In the fifth row of column 1 we show that the sensitivity of spread to sales volume is 36 basis points larger for bonds with a PL rating. This means that for a unit of additional sale's volume (where one unit is the total par value held) PL rated bonds spread widens by 36 basis points more relative to the widening in spread experienced by bonds with a public rating for a sale of similar size. By combining the primary-secondary market spread of 11 basis points with the variable component of 36 basis points (assuming a sale of the entire issuance held by insurers) we get a total liquidity component of the PLR spread premium of 47 basis points.

In the remaining columns of the table we split the sample into investment grade bonds and high yield bonds. In the first row of the column 2 we observe that the primary-secondary market spread for investment grade bonds is 21 basis points and significant at the 95 percent level, this effect is similar for high yield bonds (which we present in the column 3). In the fifth row of the column 2 we observe that for investment grade bonds the additional sensitivity of spread to sales volume is 38 basis points. The additional sensitivity for high yield bonds with a PLR, presented in column 3, is only 24 basis points, while the sensitivity of a public rating bond is 16 basis points. This findings suggest the gap in the sensitivity of price to volume between bonds with a PL rating and bonds with a public rating is larger for investment grade bonds. We caveat that the difference between investment grade bonds and high yield bonds in this dimension, while economically large, is not statistically different from zero.

For completeness in table 11 in the appendix we study if the liquidity component of PLR bias varies by asset class. There is some indication that, similarly than in the analysis in section 3.1, public bonds carry the largest liquidity risk associated with PL ratings, at least for investment grade bonds. However, the differences between asset classes, while economically large, are not statistically different from zero.

3.4 Motivation for PLR Usage

Users of private letter rated securities list keeping strategic information private as the main motivation for PLR usage (Apollo Global Management 2025) and (Zawacki 2026). However, many third parties argue regulatory arbitrage is the main driver for this practice (Tucker et al. 2025). Testing these alternative explanations is not trivial since there are no variables directly capturing PLR usage motivations. Furthermore, any characteristics we might find correlated with PLR usage might be endogenously determined.

We try to remedy this limitation by using a plausible exogenous change in regulation implemented by the NAIC in 2021. This change consisted of replacing the original 6 NAIC designations used to determine capital charges with a more granular set of 20 categories equivalent to those used by rating agencies. The details of this regulatory modification are presented in Table 1. As a consequence of this change, bonds that were originally subject to the same regulatory charge, had different charges after the modification. For example, as seen in Table 1, a BB+ bond experienced a decrease from 4.46% to 3.151% on it capital charge, while a BB- bond experienced an increase from 4.46% to 6.017%. This regulatory change had winners and losers generating heterogeneous incentives to adjust investments across insurers. In particular, companies that experienced an increase in capital charges likely had stronger incentives to shift holdings into safer instruments compared with companies that experienced a decrease in capital charges. Besides shifting assets, insurers could have also attempted to reduce capital charges by obtaining beneficial (higher) ratings without adjusting their investments' risk. Reducing regulatory requirements without reducing risk, commonly refereed to as regulatory arbitrage, has been largely documented among life insurers in extant academic work (see Becker and Ivashina (2015), Kirti and Sarin (2024), Koijen and Yogo (2016b) and Carlino et al. (2025)). The opacity of PLRs makes this type of rating a natural candidate for regulatory arbitrage.[22]

Following the methodology in Irani et al. (2021), we construct an instrument that captures the extent to which a given insurer was a "winner" or a "loser" with the NAIC regulatory change. In particular, for each insurer, the value of the instrument is the difference between their C-1 bond capital charges using the new methodology and the capital charges using the pre-reform methodology. If the regulatory change was not anticipated, we should construct the instrument using insurers' holdings as of 2020 year-end, right before the change. However, the final capital charges' structure implemented in 2021, was disclosed to insurers in 2017, 3 years in advance. Hence, to avoid potential downward bias associated with anticipation effects, we construct the instrument with holdings as of 2017 year-end.[23]

To construct the instrument for 2017 year-end bond holdings we must estimate the share of bond holdings in each of the 20 notch ratings. For bonds with public ratings we rely on 2017 year-end ratings from Mergent FISD then for the remaining bonds we use the lowest reported rating in 2020. For any bonds without a rating we construct a distribution of notch ratings for each of the 6 NAIC designation categories based on the sample of bonds with notch ratings for each insurer. This gives us an estimate of the

[22]Existing literature has documented that investor paid ratings are on average lower than issuer paid ratings (Kashyap and Kovrijnykh 2016) and (Jiang et al. 2012). However, these papers study setups where investors are trying to make informed investment decisions. In contrast, in our setup, we test the possibility that insurers purchase PL ratings to reduce capital requirements. Hence their incentives go in the opposite direction as than in Kashyap and Kovrijnykh (2016) and Jiang et al. (2012).

[23]We caveat that NAIC had made public its intention to adjust capital charges 10 years before the implementation of the change, including an initial proposal for granular risk factors in 2015. Hence, using 2017 holdings to estimate the instrument might still carry some downward bias.

dollar value of bonds in each of the 20 notch ratings held by each insurer as of year-end 2017. We then construct the instrument as the difference between the post-reform capital charges less the pre-reform capital charges as a share of 2017 corporate bond holdings.

In Figure 5 we present the effect of our instrument on the proportion of PLR bonds as a share of general account (GA) assets. The series in blue presents GA share of PLR bonds for insurers with GA assets above $1 billion, while the series in red presents the GA share of PLR bonds for insurers with assets below this threshold.[24][25] We observe that, among large insurers, the instrument already has a positive and significant effect on the proportion of investments with a PL rating in 2018. This finding supports our assumption that the regulatory modification was largely anticipated. Interestingly, among small insurers there is no effect of the instrument on rating choice until 2021, and even then the effect is statistically insignificant. One explanation could be that small insurers have limited resources allocated to regulatory compliance, and hence lack the ability to adjust beforehand. Another interesting finding is that the instrument effect is concave reaching a maximum of 11 in 2021 and disappearing completely by 2025. This means that for each additional percent of capital charges derived from the implementation of the new capital charges' methodology, insurers increased PLR usage in 11% by 2021. The dissipation of this effect by 2025 is consistent with the NAIC requirement effective January 2022, to disclose the rationale of bond rating classification and with the recent implementation of a rating contestation process. Both of these measures, described in section 2.1.1, might have made rating inflation more difficult to achieve.

In Table 9 we present the instrumental variables (IV) F-test for the parameters reported in Figure 5 as well as the correlations between observable control variables and the value of PLR bonds as a proportion of GA assets in years 2022 and 2025. The remaining years have been omitted for brevity but are available upon request. In the last row of the table we observe that the instrument's F-test for small insurers is 1.6 in 2022 and 0.02 in 2025 and hence does not meet the requirements to reject weak instruments' bias (see Stock and Yogo (2005)). In the same row we observe that, for large insurers, the F-test in 2022 is 30.62, that is well above the threshold to reject weak instruments bias. Furthermore, the F-test for large insurers rejects weak instruments' bias in all

[24] The proportion at the aggregate level is presented in Figure 13 in the appendix.

[25] The effects reported in Figure 5 come from a regression that include observable control variables.

years except from 2025. In the third and fourth rows of Table 9 we also observe that the only control variable that has a positive and statistically significant correlation with PLR usage in both years and for both small and large insurers is having private equity ownership. Having high concentration of private bond holdings, displayed in the ninth and tenth rows, is also highly significant although only for large insurers. Both of these variables have been reported in extant work as drivers of insurers' regulatory arbitrage (Kirti and Sarin 2024) and (Carlino et al. 2025).

4 Conclusion

We use a regulatory change that increased the granularity of rating categories used to set life insurer bond capital charges, and the contemporaneous proliferation of private letter ratings (PLRs), as a laboratory setup to study rating inflation. Insurers with concentrated investments in the riskier higher yielding portions of the pre-reform categories, a behavior described as regulatory arbitrage in Becker and Ivashina (2015), experience large increases in their required regulatory capital due to the reform.

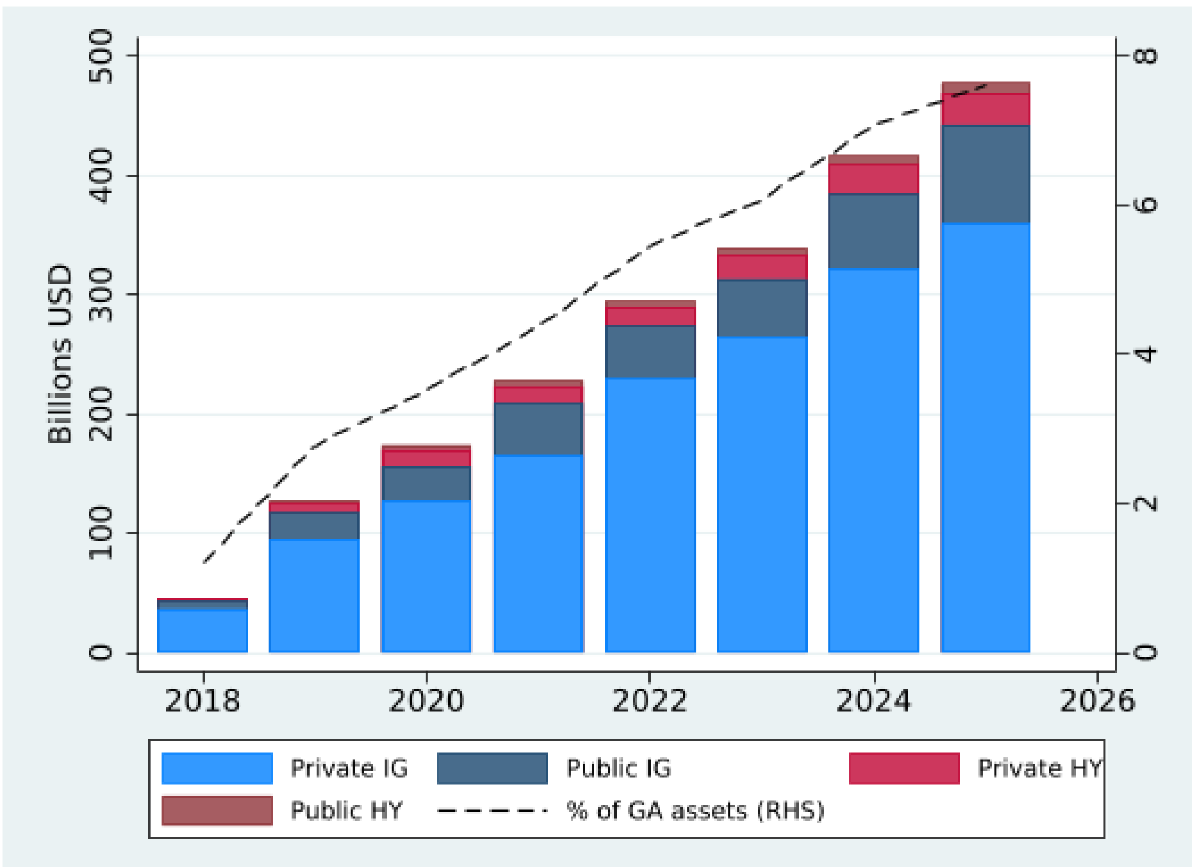
Affected insurers offset the regulatory change by using PLR agencies which provided better ratings to aggressively compete with incumbent public rating agencies. Besides creating rating inflation, private letter agencies' practices reduced rating credibility, making trading more difficult. This unintended consequence of rating inflation, while mentioned in previous research, had not been measured in extant literature.

In the sample of investment grade bonds purchased between 2020 and 2024, bonds with PLRs default 1.3% more often than comparable bonds with public ratings. The increase in regulatory capital associated with this default risk difference is equivalent to 3 rating notches. The differences in liquidity risk are of the same order of magnitude. However, since insurance regulation only focuses on default risk, the differences in liquidity risk are immaterial for regulatory purposes.

Our findings have strong policy implications. We show that besides the detrimental effects described in extant work, rating inflation might compromise the most relevant aspect of credit rating, the reduction of asymmetric information between market participants. In our framework, the reduction in liquidity due to information loss, is of the same order of magnitude as the rating inflation due to distorted expected default. Our findings, at first sight, might seem to narrowly apply to ratings of low liquidity instruments. However, history has shown that liquid instruments can turn illiquid very quickly. Measuring the magnitude and implications of this liquidity reduction in other setups, and in particular in previous recession cycles, is an important avenue for future research.

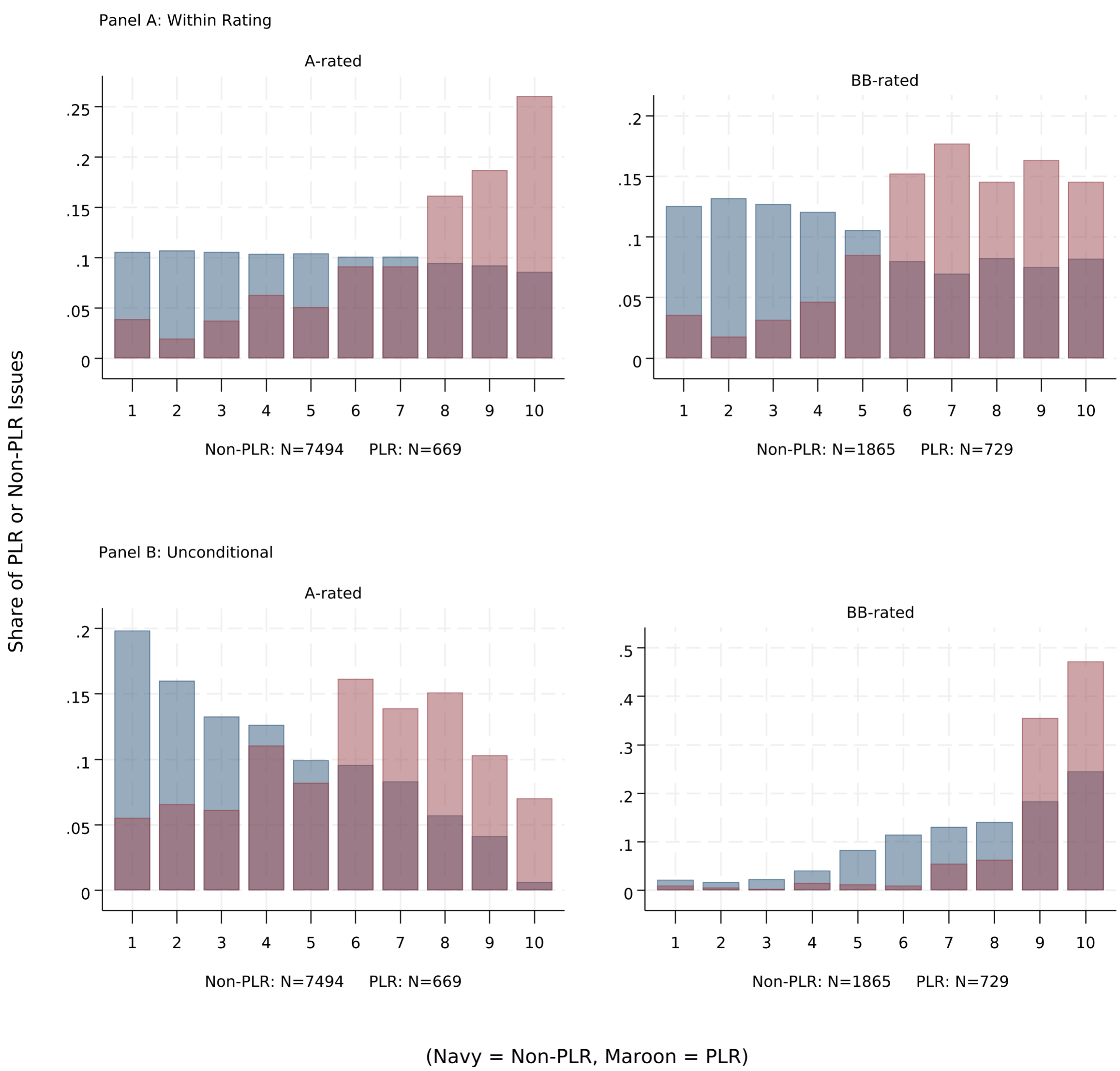
Figures

Figure 1: Life Insurance Industry PL Rated Bond Holdings: 2018 to 2025



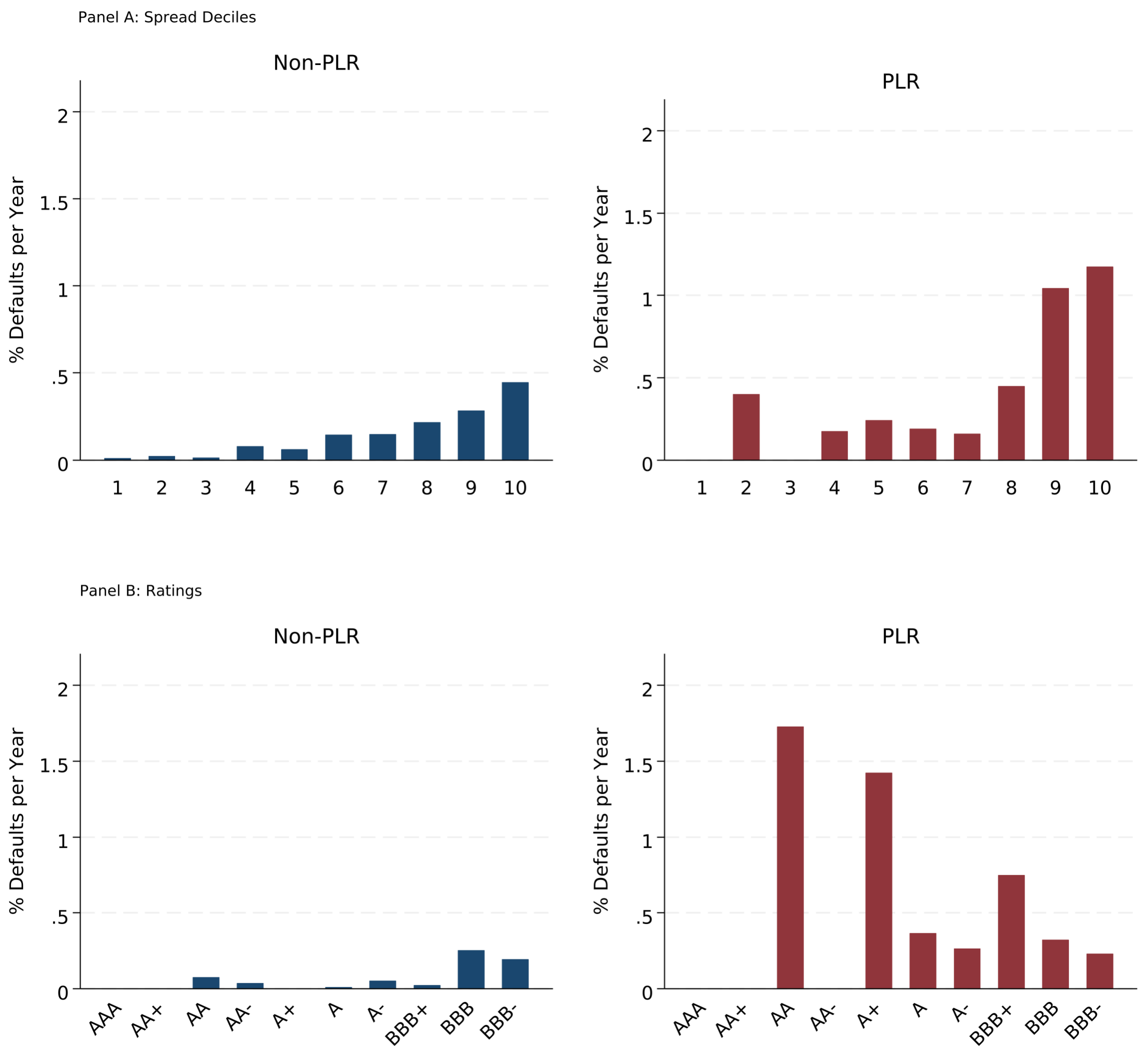
Source: Author's calculations, based on NAIC statutory filings data obtained from S&P Capital IQ Pro.

Figure 2: Distribution of A and BB Spread Deciles by PLR Status



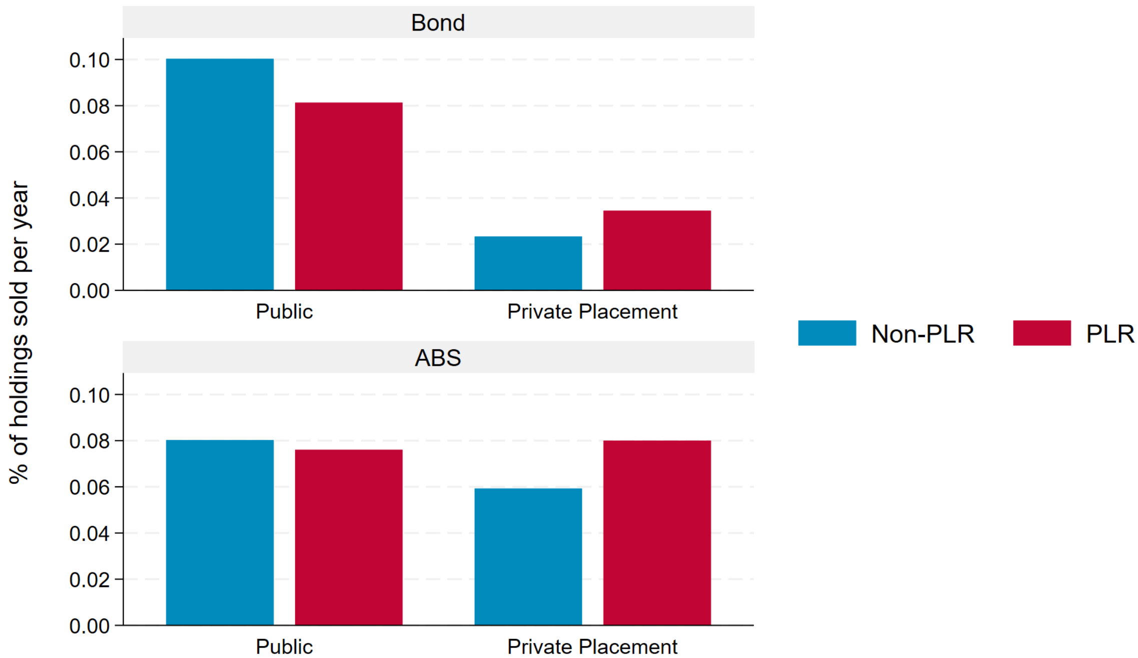
Source: Author's calculations, based on NAIC statutory filings data obtained from S&P Capital IQ Pro.

Figure 3: Investment Grade: Average Default Rate Per Year by PLR status, Spread Decile and Rating



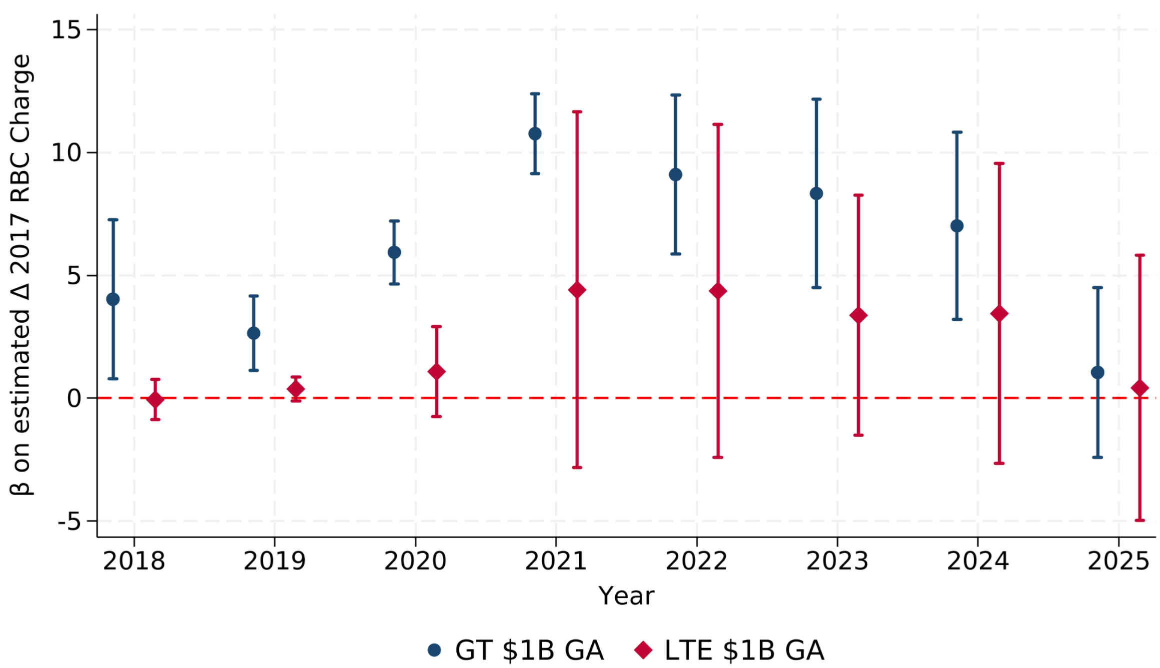
Source: Author's calculations, based on NAIC statutory filings data obtained from S&P Capital IQ Pro.

Figure 4: Weighted Average Annual sales Rate: 2018 to 2025



Source: Author's calculations, based on NAIC statutory filings data obtained from S&P Capital IQ Pro.

Figure 5: Time-Series of 2017 RBC C-1 Factor Charge Δ Coefficients by Insurer Size



Source: Author's calculations, based on NAIC statutory filings data obtained from S&P Capital IQ Pro and rating data obtained from Mergent FISD via WRDS.

Tables

Table 1
NAIC Bond RBC C-1 Factors Pre and Post 2021 Reform

Rating Equivalent	Pre 2021 NAIC Designation	Current NAIC Designation Category	Pre 2021 RBC Factor	Current RBC Factor
AAA	1	1A	0.39%	0.158%
AA+	1	1B	0.39%	0.271%
AA	1	1C	0.39%	0.419%
AA-	1	1D	0.39%	0.523%
A+	1	1E	0.39%	0.657%
A	1	1F	0.39%	0.816%
A-	1	1G	0.39%	1.016%
BBB+	2	2A	1.26%	1.261%
BBB	2	2B	1.26%	1.523%
BBB-	2	2C	1.26%	2.168%
BB+	3	3A	4.46%	3.151%
BB	3	3B	4.46%	4.537%
BB-	3	3C	4.46%	6.017%
B+	4	4A	9.70%	7.386%
B	4	4B	9.70%	9.535%
B-	4	4C	9.70%	12.428%
CCC+	5	5A	22.31%	16.942%
CCC	5	5B	22.31%	23.798%
CCC-	5	5C	22.31%	30.000%
CC and lower	6	6	30.00%	30.000%

Table 2
PLR Spread at Issue Regressions

Tables 2 shows the results of estimating equation 1. The sample includes bonds and ABS purchased by life insurers between 2020Q1 and 2025Q4. Each bond is collapsed to a single observation based on characteristics at the earliest quarter of purchase for bonds with a PL or FE designation and treated as PLR if recorded as such by any insurer. Controls include dummies for private placement, ABS, rating at issue, maturity at issue, capital structure, industry, callable, floating rate, and log of par value.

	AAA to B-	AAA to BBB-	BB+ to B-
	(1)	(2)	(3)
PLR Dummy	1.260***	1.196***	1.446***
	(0.032)	(0.037)	(0.069)
Public ABS	0.808***	0.707***	1.177***
	(0.026)	(0.024)	(0.119)
Private ABS	0.281***	0.270***	0.212
	(0.054)	(0.055)	(0.174)
Private Bond	0.325***	0.274***	0.234**
	(0.034)	(0.039)	(0.089)
Public Bond			
Quarter of Purchase FE	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	57019	45190	11829
Adjusted R-Squared	0.631	0.477	0.466

Table 3
PLR Spread at Issue Regressions

Tables 3 shows the results of estimating equation 2. The sample includes bonds and ABS purchased by life insurers between 2020Q1 and 2025Q4. Each bond is collapsed to a single observation based on characteristics at the earliest quarter of purchase for bonds with a PL or FE designation and treated as PLR if recorded as such by any insurer. Controls include dummies for private placement, ABS, rating at issue, maturity at issue, capital structure, industry, callable, floating rate, and log of par value.

	AAA to B-	AAA to BBB-	BB+ to B-
	(1)	(2)	(3)
PLR Dummy	2.216***	2.228***	2.286***
	(0.046)	(0.066)	(0.069)
Public ABS	0.913***	0.787***	1.403***
	(0.026)	(0.024)	(0.119)
Private ABS	1.359***	1.263***	1.643***
	(0.119)	(0.123)	(0.324)
Private Bond	0.938***	0.709***	1.672***
	(0.047)	(0.043)	(0.187)
Public Bond			
PLR x Public ABS	-1.635***	-1.538***	-2.404***
	(0.072)	(0.084)	(0.200)
PLR x Private ABS	-2.059***	-2.055***	-2.347***
	(0.131)	(0.142)	(0.333)
PLR x Private Bond	-1.623***	-1.540***	-2.202***
	(0.071)	(0.088)	(0.194)
Quarter of Purchase FE	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	57019	45190	11829
Adjusted R-Squared	0.640	0.490	0.484

Table 4
Spread Regression Stats: AAA to B- 2020 to 2025

	count	mean	sd	p10	p50	p90
PLR Dummy	57024	0.14	0.35	0.00	0.00	1.00
Callable	57024	0.28	0.45	0.00	0.00	1.00
Floating Rate Dummy	57024	0.29	0.46	0.00	0.00	1.00
Rating at Issue	57024	7.46	4.20	1.00	7.00	13.00
Spread at Issue (w 1/99)	57024	2.61	1.97	0.66	2.02	5.49
Public ABS	57024	0.50	0.50	0.00	1.00	1.00
Private ABS	57024	0.03	0.18	0.00	0.00	0.00
Private Bond	57024	0.09	0.29	0.00	0.00	0.00
PLR x Public ABS	57024	0.01	0.11	0.00	0.00	0.00
PLR x Private ABS	57024	0.03	0.17	0.00	0.00	0.00
PLR x Private Bond	57024	0.07	0.26	0.00	0.00	0.00
PLR x Public Bond	57024	0.02	0.16	0.00	0.00	0.00
Log Par Value	57024	16.02	1.75	13.80	16.21	18.10
Year of Issue	57024	2022.81	1.76	2020.00	2023.00	2025.00
Maturity at Issue (years)	57024	11.17	6.75	5.00	10.00	20.00
Senior Secured Debt	57024	0.30	0.46	0.00	0.00	1.00
Senior Unsecured Debt	57024	0.30	0.46	0.00	0.00	1.00
Subordinated Debt	57024	0.14	0.35	0.00	0.00	1.00
Financial	57019	0.13	0.34	0.00	0.00	1.00
MBS/ABS	57019	0.54	0.50	0.00	1.00	1.00
Non-Financial	57019	0.18	0.39	0.00	0.00	1.00
Real Estate	57019	0.01	0.12	0.00	0.00	0.00
No Industry ID	57019	0.09	0.29	0.00	0.00	0.00
Utility + Infra	57019	0.04	0.19	0.00	0.00	0.00

Table 5
PLR Likelihood of Default Regressions

	Panel A: Full Sample			Panel B: Lower Risk			Panel C: Higher Risk		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PLR Dummy	0.005*	0.005*	0.000	0.013**	0.013**	0.002	-0.000	0.001	-0.002
	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.001)	(0.002)	(0.002)	(0.003)
Spread FE	No	No	Yes	No	No	Yes	No	No	Yes
Rating FE	No	Yes	No	No	Yes	No	No	Yes	No
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample Split	Full	Full	Full	Rating	Rating	Spread	Rating	Rating	Spread
Observations	43690	43690	43690	23843	23843	21868	19847	19847	21822
R-Squared	0.010	0.015	0.017	0.019	0.020	0.007	0.012	0.015	0.019

Note 1: Table 5 shows the results of estimating equation 3. The sample includes bonds and ABS purchased by life insurers between 2020Q1 and 2024Q4 with a rating of AAA to BB-. Each bond is collapsed to a single observation based on characteristics at the earliest quarter of purchase for bonds with a PL or FE designation and treated as PLR if recorded as such by any insurer in that quarter. Controls include dummies for private placement, ABS, maturity at issue, capital structure, floating rate, and log of par value. We control for rating using a rating dummy at issue and spread using full sample spread deciles.
Note 2: Samples are split into above median (high risk) and below (low risk) median by rating and spread at first purchase. In the sample, the median rating is BBB+ and median spread is 225 basis points. We sort bonds into higher or lower risk based on whether they fall above or below the median for each sample split.

Table 6
Defaults 2020 to 2024 purchases

Rating Type		# Defaults	(%) Defaulted	(%) Defaults per year
PLR	Full Sample	64	1.04	0.55
	High Yield	30	1.32	0.80
	Investment Grade	34	0.88	0.43
Public Rating	Full Sample	172	0.46	0.23
	High Yield	119	1.65	0.87
	Investment Grade	53	0.17	0.09

Notes: Defaults are defined as any bond with an NAIC 6 designation, equivalent to CC to D rating.

Table 7
Relationship between default rates and spreads by rating

Rating	Cumulative 3-Year Default Rate (%)	Average Spread (bps)
A+	0.16	140
A	0.19	179
A-	0.22	168
BBB+	0.41	197
BBB	0.51	229
BBB-	1.17	287

Notes: 3-Year cumulative default rates from S&P Global Ratings (2025). Average spread is based on 2020 to 2025 life insurer purchases of bonds with public ratings.

Table 8
Impact of PLR on Spread (AAA to B-): 2020 to 2025

Table 8 shows the results of estimating equation 4. The sample includes bonds and ABS sold by life insurers with a with a PL or FE designation in the year prior to their sale between periods 2020Q1 and 2025Q4. Each observation is a bond sale identified in the Schedule D transactions data. Controls include dummies for most recent rating, % of bond value impaired, remaining maturity, and floating rate. We include transaction related controls for the bond's price and spread at purchase, current maturity matched Treasury rate, indicators for a direct, broker, or various sale, and quarter of sale. Standard errors are clustered at the bond - quarter of sale level.

	AAA to B-	IG	HY
PLR at Sale	0.112	0.209**	0.183*
	(0.056)	(0.059)	(0.088)
% of Ind. Par Value Sold x PLR	0.359***	0.376**	0.240*
	(0.091)	(0.120)	(0.100)
% of Ind. Par Value Sold	0.036	-0.003	0.162**
	(0.053)	(0.061)	(0.056)
Public Bond			
Private Bond	0.099	0.218*	0.134
	(0.066)	(0.078)	(0.097)
Public ABS	-0.008	0.290***	0.376*
	(0.046)	(0.055)	(0.168)
Private ABS	0.176	0.223*	0.511**
	(0.088)	(0.082)	(0.157)
Observations	159728	107217	52511
Adjusted R-Squared	0.747	0.633	0.727

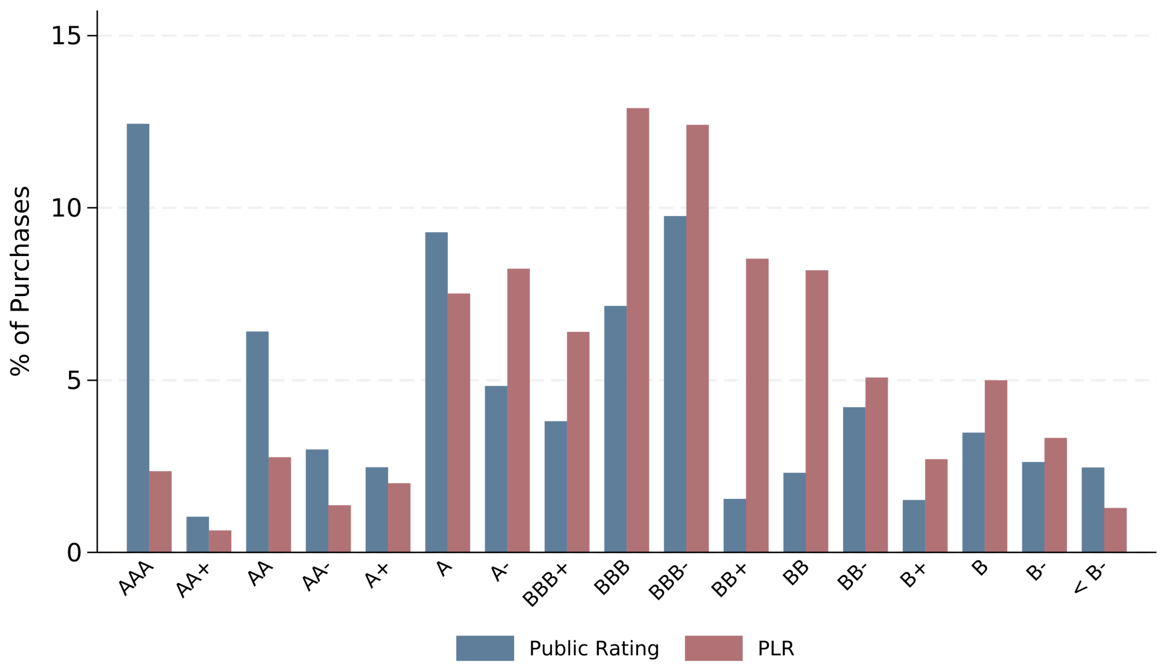
Table 9
PLR Ownership Instrument Reg: 2017 RBC Factors and 2025 PLR

Tables 9 shows the relationship between an insurer's PLR as % of general account assets and insurer characteristics including those associated with regulatory arbitrage include PE ownership, affiliated offshore reinsurance, and CLOs. The sample includes life insurance company observations of from 2018 to 2025 year-end. Standard errors are clustered at the insurer level.

	All Insurers		GT \$1B GA Assets		LT \$1B GA Assets	
	2022	2025	2022	2025	2022	2025
Δ in est. RBC C-1 (2017)	6.743**	0.797	9.101***	1.046	4.366	0.415
	(2.372)	(1.679)	(1.645)	(1.765)	(3.454)	(2.752)
PE Dummy	0.052***	0.044***	0.047***	0.043***	0.063**	0.052***
	(0.013)	(0.008)	(0.014)	(0.010)	(0.022)	(0.014)
% Rsvs Ceded to Aff	0.048	0.029	0.065	0.022	-0.012	0.075
	(0.037)	(0.029)	(0.042)	(0.028)	(0.012)	(0.123)
HY % GA	0.123	0.126	0.020	0.007	0.087	0.150
	(0.070)	(0.082)	(0.149)	(0.167)	(0.069)	(0.088)
Private % GA	0.086**	0.096***	0.128***	0.150***	0.059	0.030
	(0.028)	(0.029)	(0.037)	(0.041)	(0.037)	(0.032)
CLO % GA	0.339**	0.097	0.189	0.115	0.419**	0.147*
	(0.112)	(0.064)	(0.138)	(0.131)	(0.132)	(0.074)
Aff Assets % GA	-0.002	-0.017*	-0.039**	-0.038**	0.013	0.001
	(0.009)	(0.007)	(0.015)	(0.014)	(0.012)	(0.012)
Sch BA % GA	0.025	-0.000	0.088	0.007	-0.037	-0.042
	(0.041)	(0.031)	(0.106)	(0.101)	(0.036)	(0.026)
stock_co_2017	-0.000	-0.002	-0.010	-0.011	0.003	0.006
	(0.005)	(0.007)	(0.008)	(0.011)	(0.003)	(0.005)
RBC Ratio	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
Rtn on Assets	-0.069	-0.057	0.279*	0.100	-0.127	-0.068
	(0.061)	(0.055)	(0.131)	(0.138)	(0.066)	(0.060)
% Annuity	0.008	0.009	0.022**	0.013	-0.001	0.005
	(0.006)	(0.006)	(0.008)	(0.010)	(0.008)	(0.008)
% Indexed Annuity	0.005	0.028**	0.012	0.029*	-0.021	0.004
	(0.012)	(0.011)	(0.011)	(0.012)	(0.030)	(0.016)
Log GA	0.002**	0.003**	0.001	0.004*	0.000	-0.001
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
Observations	554	525	201	196	353	329
Adjusted R-Squared	0.324	0.256	0.342	0.190	0.237	0.124
F-stat (Instrument)	8.08	0.23	30.62	0.35	1.60	0.02

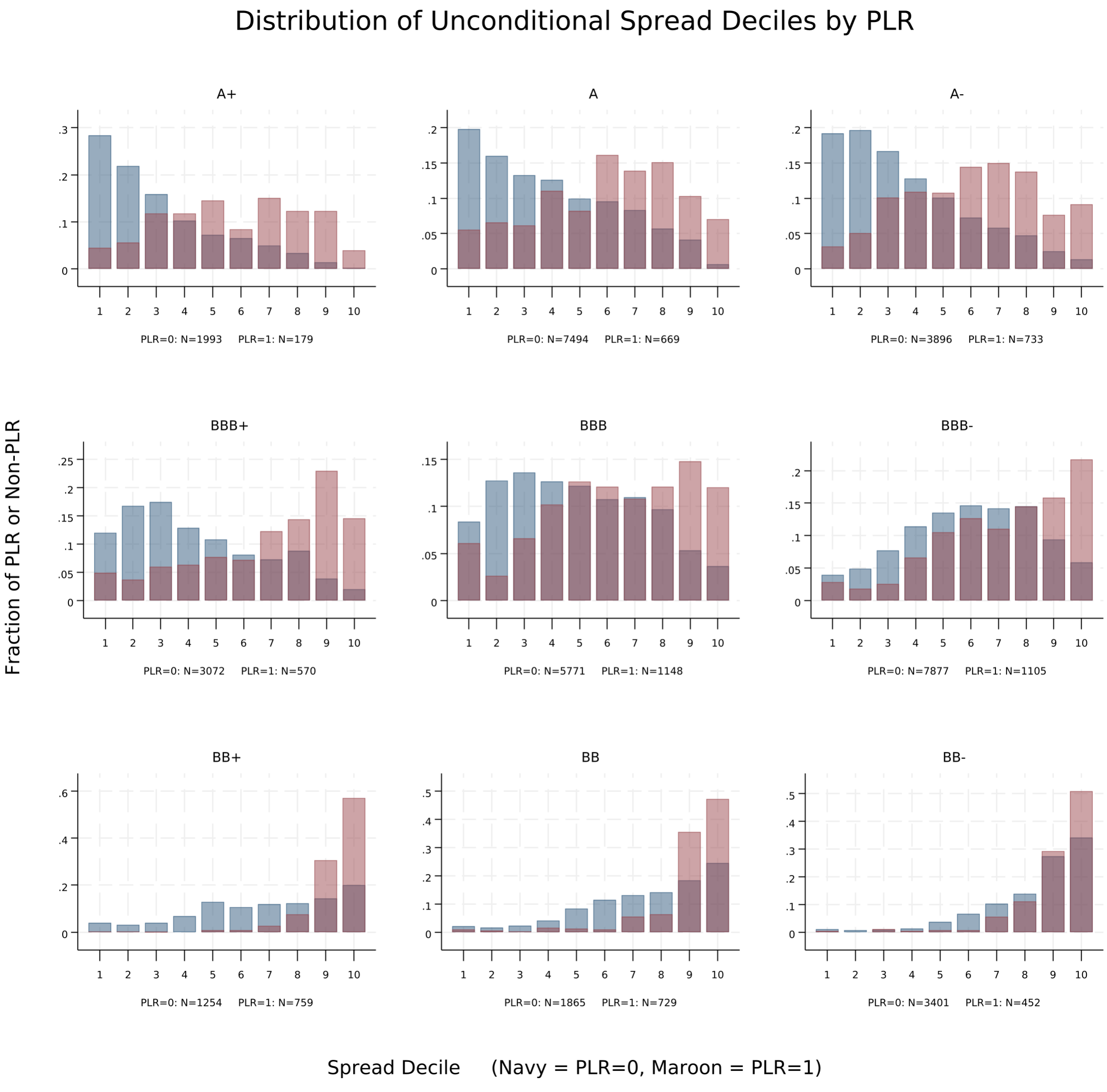
Appendix Figures

Figure 6: Rating Distribution of Life Insurer Private Letter and Public Rating Bonds



Source: Author's calculations, based on NAIC statutory filings data obtained from S&P Capital IQ Pro.

Figure 7: Distribution of Unconditional Spread Deciles by Rating and PLR Status



Source: Author's calculations, based on NAIC statutory filings data obtained from S&P Capital IQ Pro.

Figure 8: Distribution of Within-Rating Spread Deciles by Rating and PLR Status

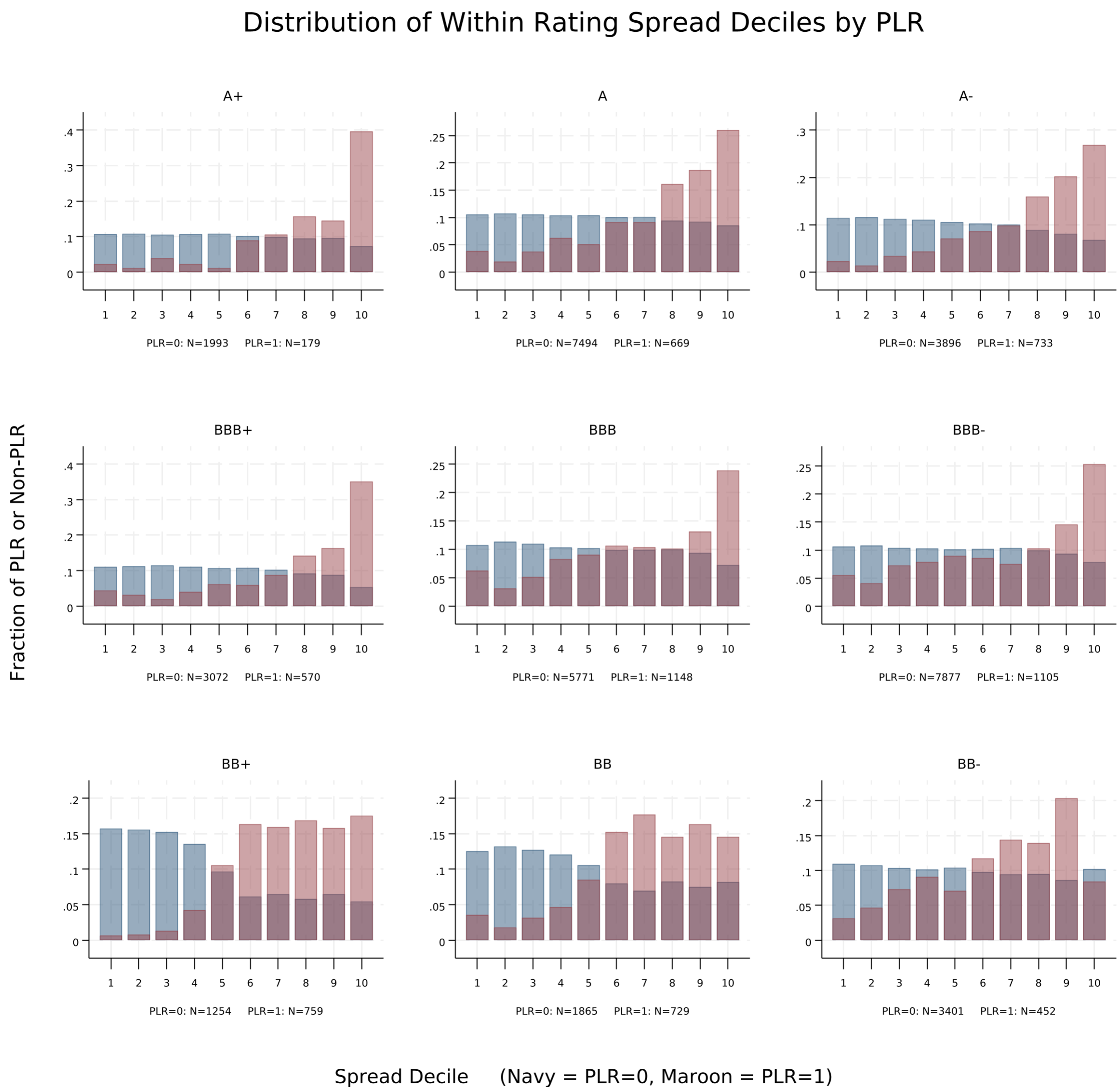
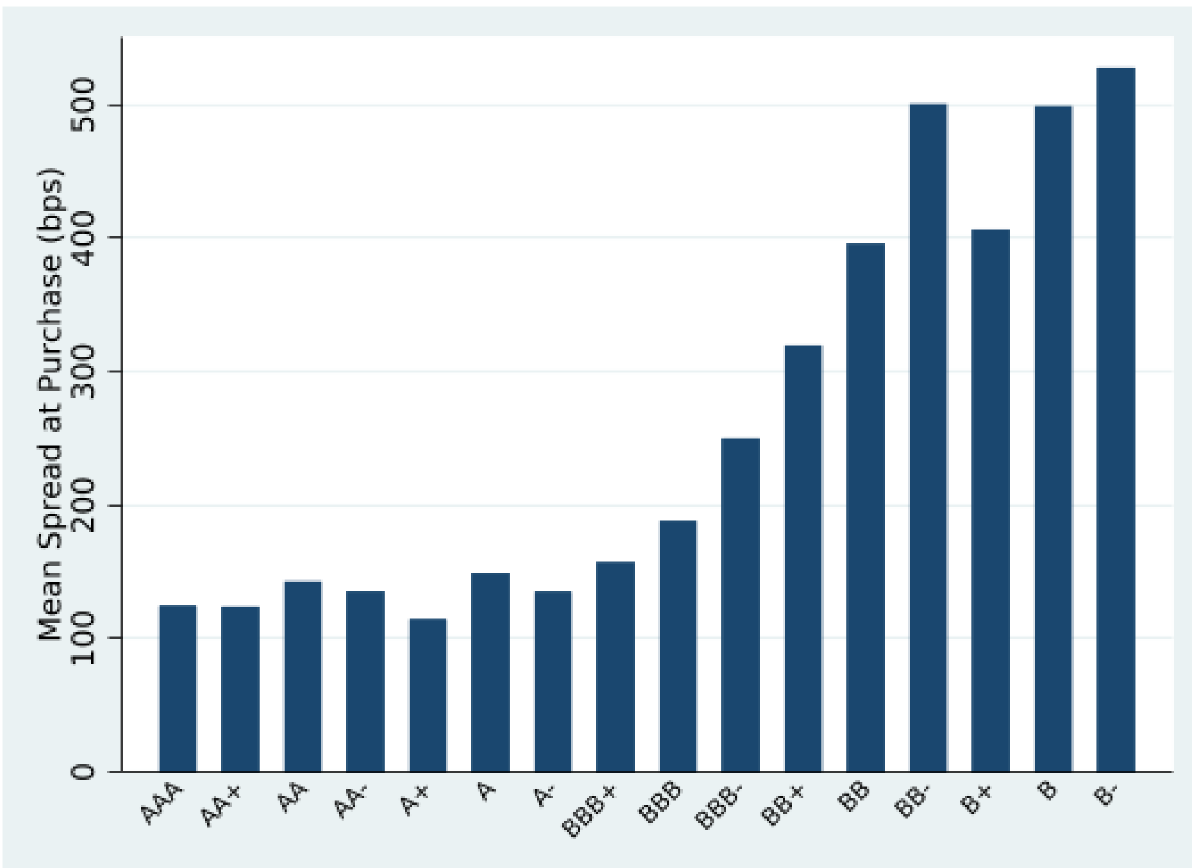


Figure 9

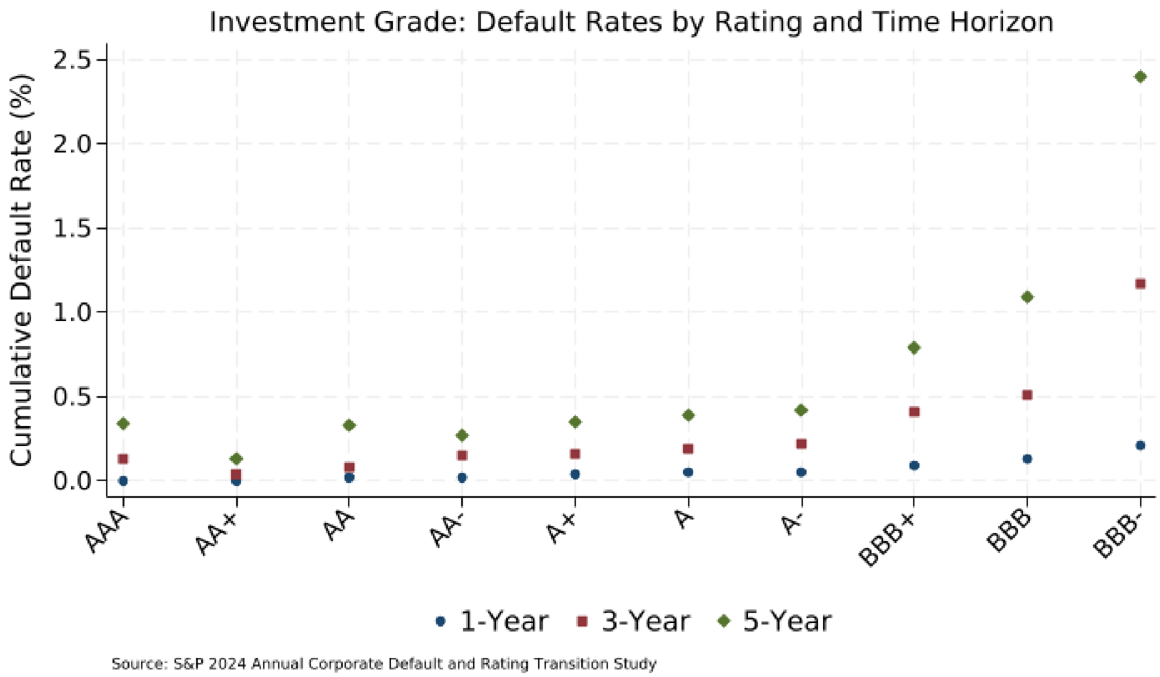
Source: Author's calculations, based on NAIC statutory filings data obtained from S&P Capital IQ Pro.

Figure 10: Average Spreads: Publicly Rated Bonds by Rating: 2020 to 2025



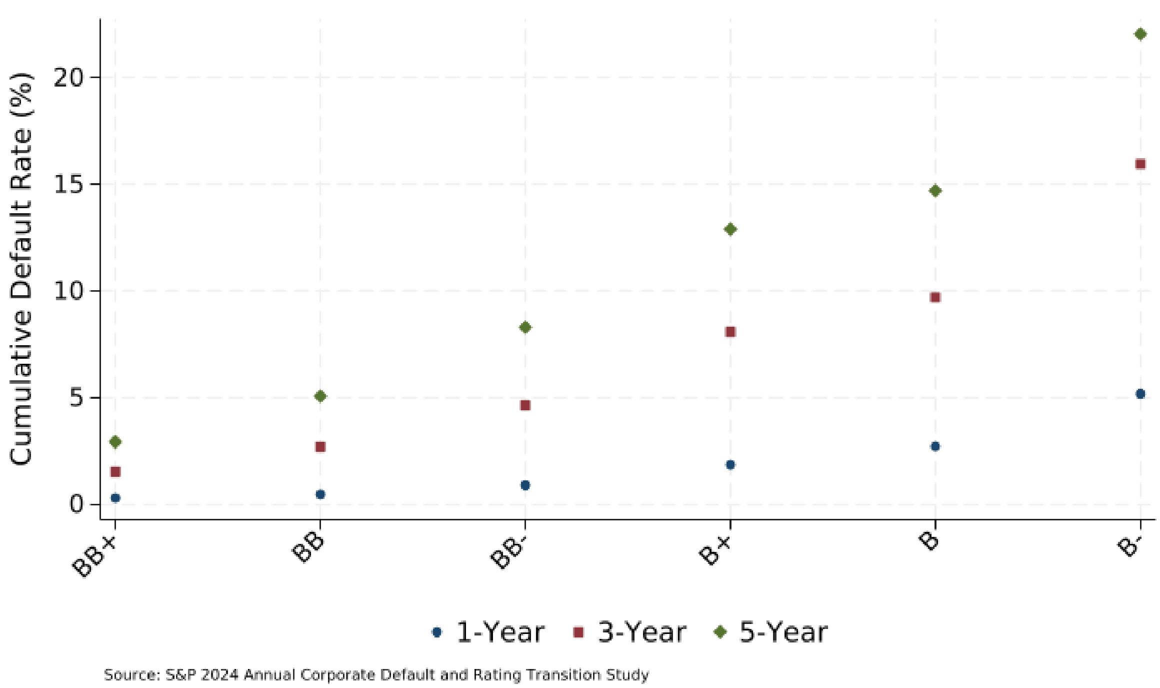
Source: Author's calculations, based on NAIC statutory filings data obtained from S&P Capital IQ Pro.

Figure 11: Investment Grade: Average Default Experience by Rating and Time Horizon



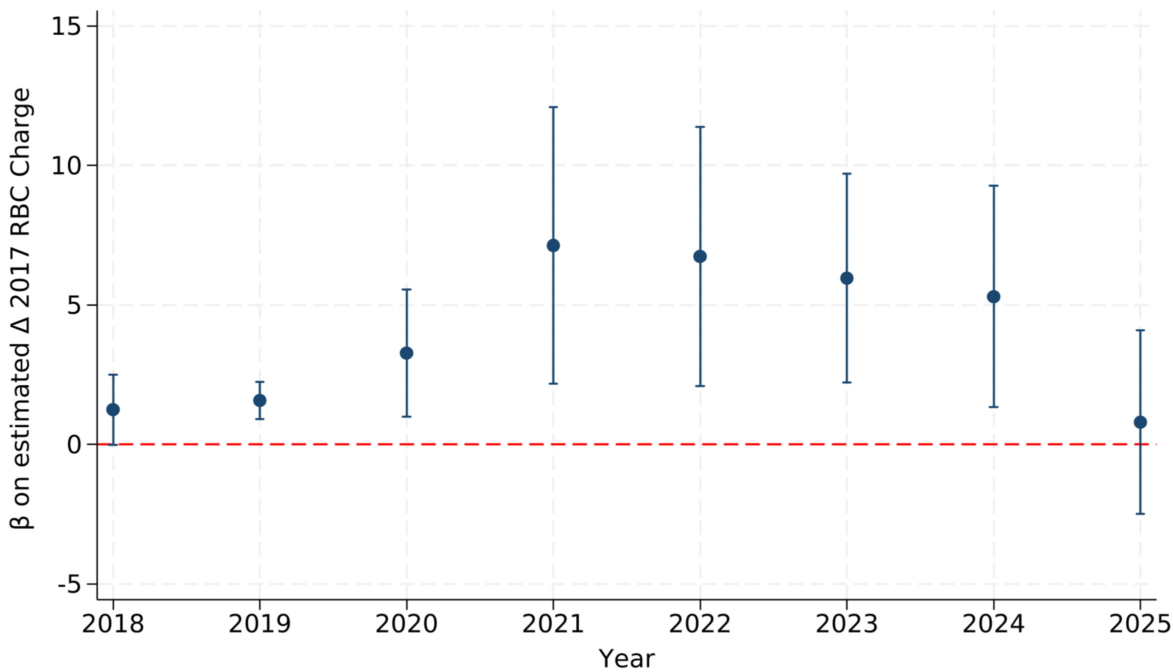
Source: Author's calculations, based on NAIC statutory filings data obtained from S&P Capital IQ Pro.

Figure 12: High Yield: Average Default Experience by Rating and Time Horizon



Source: Author's calculations, based on NAIC statutory filings data obtained from S&P Capital IQ Pro.

Figure 13: Full Sample: Time-Series of 2017 RBC C-1 Factor Charge Δ Coefficients



Source: Author's calculations, based on NAIC statutory filings data obtained from S&P Capital IQ Pro.

Appendix Tables

Table 10
Impact of 2021 Reform on 2017 Holdings: Bond RBC C1-Charges by Decile of Estimated Change

Decile	Pre-Reform Charge	Δ Post-Reform	Post-Reform Charge
1	1.14	0.17	1.32
2	1.19	0.22	1.41
3	1.10	0.24	1.34
4	1.07	0.25	1.32
5	0.97	0.26	1.23
6	1.07	0.27	1.35
7	1.12	0.28	1.41
8	1.09	0.30	1.39
9	1.10	0.32	1.42
10	1.23	0.37	1.60

Note: Based on the sample of insurers with at least $1B in GA assets.

Table 11
Impact of PLR on Liquidity Premium (AAA to B-): 2020 to 2025

	AAA to B-	IG	HY
PLR at Sale	0.273**	0.290**	0.359**
	(0.075)	(0.084)	(0.115)
% of Ind. Par Value Sold x PLR	0.337	0.599*	-0.001
	(0.176)	(0.235)	(0.250)
% of Ind. Par Value Sold	0.068	0.006	0.184**
	(0.055)	(0.068)	(0.061)
Public Bond			
Private Bond	0.213*	0.275*	0.294
	(0.102)	(0.114)	(0.153)
Public ABS	0.247**	0.296***	0.585**
	(0.068)	(0.062)	(0.198)
Private ABS	0.360	0.448	0.487
	(0.229)	(0.248)	(0.278)
Private Bond x PLR	-0.246	-0.176	-0.355
	(0.125)	(0.147)	(0.181)
Public ABS x PLR	-0.190	-0.051	-0.947**
	(0.133)	(0.154)	(0.278)
Private ABS x PLR	-0.216	-0.297	-0.147
	(0.248)	(0.261)	(0.342)
Private Bond x PV	-0.100	0.042	-0.275
	(0.143)	(0.176)	(0.211)
Public ABS x PV	-0.091	-0.033	-0.460*
	(0.061)	(0.069)	(0.197)
Private ABS x PV	0.123	0.039	0.644
	(0.386)	(0.395)	(0.633)
Private Bond x PLR x PV	0.119	-0.141	0.534
	(0.253)	(0.306)	(0.360)
Public ABS x PLR x PV	-0.105	-0.364	0.969
	(0.280)	(0.369)	(0.481)
Private ABS x PLR x PV	-0.242	-0.482	-0.343
	(0.450)	(0.466)	(0.803)
Observations	159728	107217	52511
Adjusted R-Squared	0.752	0.633	0.728

Table 12
Bond Disposal Descriptive Statistics by Bond Type

Panel A: Public Bond						
	PLR		Non-PLR		Difference	
Variable	Mean	SD	Mean	SD	Diff	t-stat
% with a Sale	0.15	0.35	0.13	0.34	0.01	2.5**
% with a Sale to Broker	0.21	0.41	0.76	0.42	-0.56	-39.2***
% with a Sale to Direct	0.43	0.50	0.08	0.27	0.35	17.8***
% with a Sale to Various	0.44	0.50	0.22	0.42	0.21	9.8***
% with a Non-Sale	0.38	0.49	0.06	0.23	0.33	20.3***
% with a Redemption	0.68	0.47	0.31	0.46	0.37	25.3***
Observations	20138		2715520			
Panel B: Private Bond						
	PLR		Non-PLR		Difference	
Variable	Mean	SD	Mean	SD	Diff	t-stat
% with a Sale	0.11	0.32	0.07	0.25	0.05	15.9***
% with a Sale to Broker	0.12	0.32	0.21	0.40	-0.09	-14.4***
% with a Sale to Direct	0.52	0.50	0.46	0.50	0.06	5.2***
% with a Sale to Various	0.42	0.49	0.37	0.48	0.05	4.2***
% with a Non-Sale	0.30	0.46	0.21	0.41	0.09	8.3***
% with a Redemption	0.63	0.48	0.54	0.50	0.08	10.4***
Observations	102299		328479			
Panel C: Public ABS						
	PLR		Non-PLR		Difference	
Variable	Mean	SD	Mean	SD	Diff	t-stat
% with a Sale	0.13	0.34	0.09	0.29	0.04	5.7***
% with a Sale to Broker	0.15	0.36	0.52	0.50	-0.37	-29.2***
% with a Sale to Direct	0.50	0.50	0.19	0.39	0.31	11.8***
% with a Sale to Various	0.45	0.50	0.31	0.46	0.14	5.7***
% with a Non-Sale	0.47	0.50	0.43	0.50	0.03	1.7*
% with a Redemption	0.19	0.39	0.04	0.20	0.15	11.4***
Observations	9532		910671			
Panel D: Private ABS						
	PLR		Non-PLR		Difference	
Variable	Mean	SD	Mean	SD	Diff	t-stat
% with a Sale	0.21	0.41	0.14	0.35	0.07	7.0***
% with a Sale to Broker	0.14	0.34	0.12	0.32	0.02	1.5
% with a Sale to Direct	0.78	0.42	0.43	0.49	0.35	17.3***
% with a Sale to Various	0.20	0.40	0.50	0.50	-0.30	-14.4***
% with a Non-Sale	0.31	0.46	0.56	0.50	-0.25	-13.1***
% with a Redemption	0.42	0.49	0.51	0.50	-0.08	-5.1***
Observations	18175		15539			

Notes: Differences in means between PLR and Non-PLR within each bond type. *** p<0.01, ** p<0.05, * p<0.10.

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